Investor Sentiment and Fund Market Anomalies: Evidence from Closed-end Fund, Exchange-traded Fund and Real Estate Investment Trust

YU, ZHIXIANG

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Zhixiang Yu

Supervisors: Dr Zhichao Zhang
Dr Frankie Chau

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Department of Economics and Finance

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University of Durham

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TO MY PARENTS

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ABSTRACT

The investor sentiment hypothesis has become a promising avenue by way of a behavioural approach to complementing conventional explanations of financial market anomalies. In response to the problems exhibited in the existing theories, the investor sentiment hypothesis has been widely tested and the results of which turn out to be able to successfully explain the market anomalies to a great extent. The thesis applies the investor sentiment theory to analysing the fund anomalies in both the UK and US markets. The test results and their interpretations may help promote a better understanding of the investor sentiment and its impacts including their geographical differences. We contribute to the literature by focusing on the sentiment measures, among others. Since the investor sentiment reflects the investors' behaviour and psychology, it is hard to be properly captured. We have constructed the proxies for the sentiment factor in both direct and indirect forms.

The first fund anomaly we analysed is the "closed-end fund puzzle". The puzzle is so-called because at IPO, the fund is issued at a premium to the net asset value (NAV); however, this premium disappears in the next few months. The fund then trades at a discount. This discount is not fixed, varying substantially during the closure period. When the closed-end fund is either converted into an open-end fund or liquidated, the discount shrinks and the share price will rise. We construct an out-of-sample test by using the two-factor and five-factor models. The results show that the investor sentiment can contribute to explaining closed-end fund discounts in the UK market and it is more prevalent in smaller size portfolios. We also find the evidence to support investor sentiment as an important factor to represent systematic risk in the return generating process.

Next, we examine the price deviations of Exchange Traded Funds (ETFs). Unlike closed end funds whose prices also deviate from the NAV, ETFs, through a mechanism known as redemption in-kind, allow institutional investors to potentially earn a profit by arbitraging away these price deviations through creating and deleting outstanding shares of the ETF. Hence, we are motivated to identify the factors that may impact on the determination of these premiums and discounts to the NAV. We first construct a sentiment proxy from the derivative market variables such as the option put–call trading volume ratio and the open interest ratio. Then we develop a sentiment proxy based on the consumer confidence index, obtained from the mainstream consumer surveys and this proxy is taken to the individual fund level. The results provide evidence that this sentiment proxy has explanatory power for most individual ETF mispricing. We take the whole industry into account and find that the sentiment factor has incremental explanatory power and is positively related to the fund premium. The evidence also shows that more sentiment-sensitive ETFs are those that have smaller, younger and volatile stocks with low dividend yields.

Finally, the thesis considers the fund anomaly in the form of the REIT price momentum. In order to investigate the momentum profitability, we classify the formation period into two sentiment states, i.e. the optimistic and pessimistic periods. Evidence indicates that when sentiment is high, the REIT momentum profitability is substantial and significant; however, when the sentiment is low, the profits from the REIT momentum are much lower and not significant. We also examine the interplay between REIT liquidity and momentum profitability. We find that high REIT liquidity portfolios generate higher momentum returns, but this is only significant when the sentiment is optimistic. Furthermore, consistent with our previous findings, our evidence that momentum is generally larger for smaller companies confirms that the size effect is still available in the REIT industry. This is because the smaller companies are often difficult to value, as they are more prone to subjective evaluations. The sentiment thus could be more significant in small size companies.

DECLARATION

The content of this thesis is based on the research work completed at Durham University Business School, UK. No material contained in the thesis has previously been submitted for a degree in this or any other university. It is all my own work unless referenced to the contrary in the text.

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CHAPTER 1

INTRODUCTION

1.1 Overview and Motivations

Most researchers are paying more attention to the investor sentiment hypothesis recently and the related theories have been developed in the last few years mainly due to a seminal paper published by Lee, Shleifer and Thaler (1991), who construct a model of investor sentiment based on behavioural finance perspective to try to explain the perplexing anomalies in the literature. They proposed that the predominant holders of closed-end funds are individual investors, and some of them are noise traders who exhibit irrational performance in their expectations and trading about future fund returns. In their theory, when noise traders are optimistic on their trading assets and enhance the prices; other times, noise traders are pessimistic, then the prices would be driven down and closed-end funds sell at relatively larger discount. The investor sentiment explanations seems to outperform than alternative theories in explaining the perplexing anomaly. In response to the problems exhibited in the existing theories, the investor sentiment hypothesis has been widely tested and the results of which turn out to be able to successfully explain the market anomalies to a great extent. The thesis applies the investor sentiment hypothesis to analyse the fund anomalies in both the UK and US markets. The test results and their interpretations may help promote a better understanding of the investor sentiment and its impacts including their geographical differences. We contribute to the literature by focusing on the sentiment measures, among others. Since the investor sentiment reflects the investors' behaviour and psychology, it is hard to be properly captured. We have constructed the proxies for the sentiment factor in both direct and indirect forms.

My research was initially motivated by the shortcomings of the traditional finance paradigm. In this framework, it seeks to explain the financial markets based on the models that agents are "rational" and it states that the security prices in financial markets should be equal to the fundamental values and this perspective has been the central proposition in finance for decades. Nevertheless, after years of investigation and study, it has become clearer that this conjecture facing the fact that it cannot make us understand the financial markets and individual trading behavior fully and easily. Specifically, despite these theories can explain some financial anomalies to a certain extent; however, none of them provides satisfactory explanation for all aspects of the anomalies because it is pointed out that each of the rational theories fails to account for a great deal of the existing evidence. The failure of the traditional finance theory to explain the anomalous behavior accelerates the development of an alternative approach which attempts to explain how the cognitive errors and psychology changes influence investor decision making process. Many researchers believe that behavioural finance is a developing perspective to the study of financial markets that has emerged, at least in part, in response to the perplexing problems encountered by the classical theories. This developing perspective motivates me to shed light on the market anomalies by the behavioural approach.

Secondly, behavioural explanations are now lighting up the world of finance research as they attempt to explain any anomaly in the literature. Besides, the fund market is growing rapidly and becoming more popular, as a professional investment tool, it is interesting to link the fund anomalies to the new behavioural perspectives. In order to make sharp predictions on the investment, we often need to specify the form of investors' irrationality. The outcome of my research may give rise to potential opportunities for exploiting the relationship between the fund price anomalies and investor behaviours. Understanding the underlying mechanisms and influential factors of the fund price performance, can guide fund managers in their management and investment decisions. By undertaking this kind of fund market research, it will be possible to advise investors better regarding fund and stock markets, so that they can make their decisions much more skilfully and so reduce their investment risk. At the same time, the analysis of difference fund market anomalies will not only help guide management and investment decisions, but since the impact of these anomalies involves the same factors as those related to other securities, it will also have great significance for all kinds of financial investors.

My third motivation originates from the imperfection of the existing investor sentiment measures. Since the investor sentiment reflects the investors' behaviour and psychology, it is hard to be properly captured. It will benefit us to examine the investor behaviour and it impact on the securities if we can construct a good proxy for investor sentiment. The existing measures of sentiment, ordered from origins in investor psychology to responses by corporate insiders, include: surveys, mood proxies, retail investor trades, mutual fund flows, trading volume, dividend premia, closed-end fund discounts, option implied volatility, first-day returns on initial public offerings, volume of initial public offerings, new equity issues, and insider trading.[1] Generally, the proxies for sentiment factor are from direct and indirect ways. Specifically, the direct measure is formed from the consumer confidence survey results. These surveys are conducted by the UK and US institutions which investigate into the

[1] See Baker and Wurgler (2007), they comment on these sentiment proxies respectively and then choose among them.

consumer behaviour and expectations. The indirect measure is related to constructing the sentiment index by considering macroeconomic influences. According to the specific characteristics of the fund markets and firms, we cannot replicate these measures and need to choose among them or construct new proxies for our research.

1.2 Fund Market Anomalies

Anomalies are empirical results that seem to be inconsistent with maintained theories of asset-pricing behaviour, specifically, they show deviations from the Efficient Markets Hypothesis (EMH)/Capital Asset Pricing Model (CAPM) paradigm. The term anomaly can be traced to Kuhn (1970). The anomaly indicates either market inefficiency (profit opportunities) or inadequacies in the underlying asset-pricing model.

In the fund markets, although both CEFs and open-end funds are actively managed pooled investments, in contrast with open-end fund trading at their Net Asset Value (NAV), the CEFs are always traded at a price under or above the NAV. The deviation from the NAV constitutes a discount or premium, known as the closed-end fund puzzle, which is a hot issue in the "anomalies" of the fund market. Besides, our main focus in the fund market is the identification of anomaly in relation to the price deviation that exists in the underlying stocks the Exchange Traded Funds hold (see for example Switzer, Varson and Zghidi,2000; Hedge and McDermott, 2004 and Ackert and Tian, 2000). Moreover, Jegadeesh and Titman (1993, 1999) show that stocks with strong past performance would continue to outperform stocks with poor past performance in the next period with an average excess return of about 1% per month. The price momentum is another market anomaly, which traditional finance theories are struggling to explain. The momentum effect is also captured to be significant in REITs. Chui et al. (2003) find significant momentum in the U.S. REITs from 1983 to 1999. Derwall (2009) finds strong evidence to support for performance persistence in REITs. Hung and Glascock (2008) document that the REIT momentum is positively related to volatility and they find that idiosyncratic risk can partially explain momentum.

1.2.1 The Closed-end Fund Puzzle

The history of closed-end funds (CEFs) began from 1893 in the US, which is more than 30 years before the first mutual fund was generated. By 2013, there are around 650 CEFs traded on the US market.[2] In the UK, the first closed-end fund was launched in 1868 by Foreign & Colonial, which is listed on the London Stock Exchange. Since then, the UK CEF industry has developed substantially.

A close-end fund is a collective investment scheme under professionally management of an investment company. The fund issues a fixed number of shares and unlike open-end funds; the shares of such a closed-end fund can be only purchased/sold in the market by the fund investors. That is, the investors who want to buy a share of the closed-end fund can only go to the exchange and buy it from other investors at the prevailing price (Barberis and Thaler, 2002). Although both CEFs and open-end funds are actively managed pooled investments, in contrast with open-end fund trading at their Net Asset Value (NAV), the CEFs are always traded at a price under or above the NAV. The deviation from the NAV constitutes a discount

[2] The sources are from the CEFA website and the figures shown above are current as of September 2013.

or premium, known as the closed-end fund puzzle, which is a hot issue in the "anomalies" of the financial market.

In practice, the CEF discount is not fixed, since it trades at a discount about 10% on average, and this discount varies substantially over the time (Thompson, 1978). When the CEFs are created, the share price is usually above the NAV, so they are traded then at a premium (Weiss, 1989 and Peavey, 1990). However, when they are terminated, either through liquidation or open-ending, the price will be close to NAV (Brauer 1984).

A large number of researches have attempted to explain this anomaly. Initially, the solutions that researchers put forward are based on rational theories. These include agency costs (Boudreaux, 1973; Ross, 2002), illiquidity of assets Seltzer (1989), and tax liabilities Brickley, Manaster and Schallheim (1991, among others. Although these findings may explain the CEF discount puzzle to some extent, there remain many aspects of the CEF discount puzzle that are unaccounted for. In this light, an alternative approach based on behavioural theory has been developed in the past decades to fill the gap, which helps us achieve a better understanding of the anomaly of this kind. In this approach, researchers believe that investors' psychology and other behavioural issues replenish the efficiency of financial market and may explain many of the financial anomalies.

Zweig (1973) and Delong et al. (1990) attempt to use the behaviour approach to give an alternative explanation for the puzzle; specifically, Zweig (1973) is the first to suggest that discounts of the closed-end funds reflect expectations of individual investors. Delong et al.

(1990) suggest that the discount of CEFs can be viewed as the result of fluctuations of investors' expectations, which change the demand structures of CEF shares and produce a noise trader model to support their points. Lee, Shleifer and Thaler (1991), or LST hereafter, propose a simple investor sentiment theory to explain the CEF discount puzzle. They suggest that most of the investors who trade in CEFs are noise traders. These investors are prone to hold irrational expectations about the fund's future returns. Changes of the investor sentiment impact on CEF trading prices and induce CEF prices to change over time. Specifically, when the investors are optimistic about future returns, the sentiment is high and there is premium on CEFs while there is a discount when they feel pessimistic about the market conditions.

This explanation helps us understand the main driving force behind the CEF puzzle. The companies that issue the CEFs tend to crowd together in the time of investor exuberance. During this period, they would believe that the CEFs could be sold for more than their intrinsic value and the discount on CEFs could be lower than normal. On the other hand, when the CEFs are either turns to be open-ended or liquidated, rational investors do not need a compensation for assuming the noise trader risk; because they know that the CEF share price will be close to NAV.

1.2.2 Exchange Traded Fund Price Deviation

Exchange Traded Funds (ETFs) are an emerging investment product. They are becoming substantially important and popular in the index mutual fund product category. Such funds are investment hybrids of open-ended fund and common stocks. They hold a fixed basket of stocks based on an underlying index, with identical stocks and weights, but they trade throughout the day at market-determined prices on a stock exchange. ETFs are attractive to many investors due to their low costs, tax efficiency, and stock-like features.

In January 1993, the first ETF was introduced in the US. This ETF is Standard and Poor's Depository Receipts, also known as Spiders (SPDRs), which tracks the holdings and returns of the S&P 500. Other popular ETFs include DIAMONDS (DIA) and Qubes (QQQQ), which track the Dow Jones Industrial Average (DJIA), NASDAQ 100, respectively. They began trading in 1998 and 1999. Since then, the industry has undergone tremendous growth. There are now more than two trillion dollars invested in over 4,500 ETF products worldwide.[3]

ETFs are similar to stocks; they can be traded on the exchange either by shorting or buying on margin. ETF products can track a wide variety of indexes, including not only the broad indexes of general stock and bond markets, but also industry sectors and international stock indexes. The ETFs do not give investors the opportunity to outperform the returns of the underlying index, however. With these peculiar features, ETFs have received a great deal of attention in the academic and practitioner communities.

Recent literature has studied the impacts of ETFs' issuance on financial markets. The main focus is the identification of anomaly in relation to the price deviation that exists in the underlying stocks these ETFs hold (see for example Switzer, Varson and Zghidi,2000; Hedge and McDermott, 2004 and Ackert and Tian, 2000). Besides, Ackert and Tian (2000), Elton et al (2002), Poterba and Shoven (2002), investigate in the ETF pricing and performance which includes, but not limited to, the ETF pricing that differs from the NAV pricing. Although the

[3] Source: BlackRock: ETP Landscape: Industry Highlights (January 2013).

ETFs are traded in the way like CEFs, it is of interest that ETFs, through a mechanism known as redemption in-kind, allow institutional investors to potentially earn a profit by arbitraging away these pricing deviations through creating and deleting outstanding shares of the ETF. This creates the opportunity to test whether ETFs could be affected by investors' biases, or other risk factors.

1.2.3 REIT Price Momentum

REIT stands for the Real Estate Investment Trusts, which is a type of real estate companies that modeled after mutual funds. REITs were introduced by American Congress in 1960 to provide an opportunity for investors to invest in real estates in a manner similar to stocks and bonds traded through mutual funds. REITs may invest in the properties themselves or in mortgage or mortgage-related securities tied to the properties. The trading of REITs is like that of the common stocks. After paying a conversion fee, a REIT escapes corporation tax. It must pay out 90% of its property income to shareholders annually in the form of dividends. With assets of more than $650 billion[4], publicly listed REITs are traded in the US on all major stock exchanges and they offer both individual and institutional investors the opportunity to diversify their portfolio risks.

In the finance literature, momentum is the empirically observed tendency for rising asset prices to rise further, and falling prices to keep falling. Jegadeesh and Titman (1993, 1999) show that stocks with strong past performance would continue to outperform stocks with poor past performance in the next period with an average excess return of about 1% per month. The momentum is a market anomaly, which traditional finance theories are struggling

[4] Asset total is from www.nareit.com as of January 31, 2013.

to explain. The momentum effect is also captured to be significant in REITs. Chui et al. (2003) find significant momentum in the U.S. REITs from 1983 to 1999. Hung and Glascock (2008) document that the REIT momentum is positively related to volatility and they find that idiosyncratic risk can partially explain momentum. Derwall et al (2009) finds strong evidence to support for performance persistence in REITs.

Controversies exist in the explanation of REITs' price momentum. The contention documented in the previous study can be classified into three general categories: theories of market frictions (Hong and Stein, 1999), theories of time-varying expected returns (Johnson, 2002), and behavioural theories of market inefficiency (Daniel, Hirshleifer, and Subrahmanyam, 1998). Much of the existing financial research attributes the appearance of momentum to the investor biases. Delong et al (1990) suggest that the noise traders who lack of fundamental information are likely to be trend-chaser, reinforcing the movements in stock prices. Another behaviour explanation is rejated to the underreaction theory which has been documented in Chan et al (1996), Barberis et al (1998), Daniel, Hirshleifer, and Subrahmanyam (1998, DHS hereafter), and Hong and Stein (1999). The authors suggest that price momentum strategy may benefit from the market's slow response to a broader set of information, including longer-term profitability. DHS (1998) suggest that the momentum effect is generated by investors' overconfidence and self-attribution bias. These studies motivate us to further explore the investor sentiment, which may provide an alternative yet plausible explanation for the momentum of fund prices by way of examining the REIT price momentum.

1.2.4 Behavioural Finance Overview

Behavioural explanations are now lighting up the world of finance research as they attempt to explain any anomaly in the literature, so as a broad area it is interesting, and has recently been on the cutting edge of finance which involves a simple behavioural approach. Behavioural finance is a developing perspective to the study of financial markets that has emerged, at least in part, in response to the perplexing problems encountered by the classical theories. Contrary to the EMH and CAPM, it announces that by using the models in which not all the agents are fully rational.

Black's (1986) theory of "noise traders" suggests that sometimes they trade without information, and as a result they are incorrect and irrational; these behaviours lead to noise trading, these investors cause the market to be inefficient, but often prevent us from taking advantage of inefficiencies. De long, Shleifer, Summers and Waldmann (1990) (DSSW henceforth), present a model of noise trader survival in perfectly competitive market conditions, noise traders are optimistic on their trading assets and enhance prices; at other times, noise traders are pessimistic about the returns on securities, so the prices are driven down. Less than fully rational investors could be able to affect the price, and these noise traders play a key role in our financial markets, which poses a huge challenge to the traditional efficient market hypothesis. Lee, Shleifer and Thaler (1991), or LST hereafter, suggest that most of the investors who trade in funds are noise traders. These investors are prone to hold irrational expectations about the fund's future returns. Changes of the investor sentiment impact on the fund trading prices and induce fund prices to change over time. Barberis and Thaler (2002) presents a number of behavioral finance applications: to the aggregate stock market, to the cross-section of average returns, to individual trading behavior, and to corporate finance.

1.3 Contribution and Main Findings

In the past few decades, the application of traditional finance theory to the explanations of market anomalies has been faced with huge challenges. In order to improve the weak explanatory power of conventional factors, the investor sentiment hypothesis first proposed by LST (1991) has become a promising avenue by way of a behavioural approach to complement the conventional explanations of financial market anomalies. In response to the problems exhibited in the existing theories, the investor sentiment hypothesis has been widely tested (Neal and Simon, 1998; Qiu and Welch, 2005; Kumar and Lee, 2006; Baker and Wurgler, 2007) and the results of which turn out to be able to successfully explain the market anomalies to a great extent.

The existing investor sentiment literature has primarily focused on the stock market performance, especially that of the US market. Few past studies have been concerned with the fund market anomalies. The current research in this thesis not only investigates the fund market but also attempt to explore the role that investor sentiment may play in the UK fund market. Furthermore, our research also bridges the gap in the literature by applying the sentiment approach to explain the market anomalies within both the UK and US markets.

The contributions that this study makes to the existing literatures include the following. First, our study is among the first to apply the investor sentiment theory to the fund anomalies in the UK market. A small number of studies have examined the investor sentiment in the fund market (Levis and Thomas, 2000; McLean and Zhao, 2009). They however failed to extend the research to the anomalies observed in the fund market pricing and performance, while the fund industry is developing rapidly. Understanding the underlying mechanisms and influential factors of the fund price performance can guide fund managers in their management and is beneficial to individuals' making of better investment decisions. A related contribution of our work lies in our investigation of the sentiment outside of US market. Since most investor sentiment studies are sampled in the US capital market, it cannot be ruled out that the results may be limited to the US case only. The test of sentiment theory in this thesis may give us a better understanding of the investor sentiment and its impacts based on the geographical difference. Finally, we contribute to the literatures by focusing on the sentiment measures. Since the investor sentiment reflects the investors' behaviour and psychology, it is hard to be properly captured. We have constructed the proxies for sentiment factor in both direct and indirect forms. Specifically, the direct measure is formed from the consumer confidence survey results. These surveys are conducted by the UK and US institutions which investigate into the consumer behaviour and expectations. The indirect measure is related to constructing the sentiment index by considering macroeconomic influences, such as the closed-end fund discount, and the put-call ratio in the options market.

Along these lines, an analysis of the theoretical foundations and empirical research on the data are attempted. Our results confirm that investor sentiment has significant impacts on fund market risk premium and the changing sentiment of individual investors can explain the discounts of closed-end funds in the UK market and this sentiment is sensitive to the size. Moreover, sentiment is likely to be generated from concentrated individual ownership. The investor sentiment has an explanatory power for most of UK ETF price deviation and ETFs with different characteristics are sensitive to the investor sentiment in different ways. For the US REITs, we conclude that sentiment is significant to their momentum when it is optimistic. However, the momentum returns decline substantially when sentiment is pessimistic. We also find that investor sentiment can explain REITs' short-run continuation and long-run reversal. Further, under different size and liquidity portfolios our results are robust as well.

According to the empirical results, our theoretical contribution encompasses some aspects of the behavioral explanations on the fund market anomalies which is developed by the limited rationality model of LST (1991). Investor sentiment is defined as an aggregate measure of investors' attitude toward market conditions and can be classified as pessimistic, neutral and optimistic. The examinations on investor sentiment generally investigate investors' expectations which refers to "noise traders" or irrational investors, investor sentiment studies generally either support of refute whether non risk related measures have the ability to change some fundamental aspects of the funds such as price.

We address that the irrational individual investors, the most dominant holders of closed-end fund shares, trade their assets by an additional risk, the misperceptions of these investors place them into optimistic or pessimistic overreactions. The risk of fund investment is systematic and holding the fund is risker than holding their portfolios directly. Consequently, investors require higher returns on the assets of funds than on the underlying asserts traded directly. This theory can explain why the closed-end funds must sell at a discount to the net asset value. Furthermore, the discount of funds and other securities (such as small stocks) are affected by the same sentiment, the changes of the sentiment should cause changes in discounts and the fluctuation of discounts should be highly correlated across funds. We confirm the small firm effect in investor sentiment theory, i.e. the discount in closed-end fund industry is more likely to be influenced by smaller firms than by large firms, since the noise traders concentrate their holdings and trading activities in small firms, low priced firms and lower institutional ownership firms. This conjecture can also explain that why the different sectors of securities have the different level of the discounts. Similarly, we suggest that the investor sentiment have the significant effect on the pricing of UK ETFs, and it can impact the pricing of the ETFs at different level by various characteristics of the ETF firms.

Momentum in stock prices is proposed in a seminal work by Levy (1967), which concludes that buying stocks that are historically comparatively strong can attain profitable results. By extending this work into the fund market, our study in REIT price momentum contributes to the notion theoretically that REIT short-run momentum and long-run price reversal jointly arise from investors' behavioral biases and is robust when controlling for firm size and trading volume.

1.4 Organisation of the Thesis

This thesis comprises five chapters that is centred on three main essays. All of the three essays attempt to better our understanding of the interplay between investors and fund markets, in particular between the investor perceptions and potential biases and market anomalies. The investor perceptions of the market are proxied by measures of investor sentiment through which we analyse their impacts on the fundamental aspects of CEFs, ETFs and REITs. The structure of the thesis is as organised as follows:

- **Chapter 2:** investor sentiment and closed-end fund puzzle. In this chapter, we investigate whether the investor sentiment plays a significant role in the formation of closed-end fund discount, and hence its impacts on stock risk premium in the UK market.

- **Chapter 3:** investor sentiment and ETF price deviation. Chapter 3 examines the relationship between investor sentiment and ETFs' price deviation from the fundamentals in the UK market. We also investigate the relation of the sentiment and different ETF characteristics.
- **Chapter 4:** investor sentiment and REIT price momentum. Chapter 4 estimates the REIT momentum returns in different investor sentiment states. Such analysis sheds empirical lights on whether investor sentiment affects the profitability of REIT price momentum strategies in the US market.
- **Chapter 5:** Conclusions. In this final chapter, we summarise the results of this work as well as give suggestions for future research.

CHAPTER 2

CLOSED-END FUND PUZZLE AND INVESTOR SENTIMENT

2.1 Introduction

Closed-end funds are funds which issue a fixed number of shares after the initial public offering (IPO). Unlike the more familiar open-end funds, which can issue new shares and sell to buyers at the net asset value (NAV), the per share market value of its asset holdings,[5] the price of a share in a closed-end fund is determined not just by the value of the assets in the fund, but also by the market demand; thus shares can be traded either below their NAV (discount) or above it (premium). Investors who wish to buy a share of such funds can do so only by buying from other investors at the prevailing price (Barberis and Thaler, 2002).

The discounting of closed-end funds is a common anomaly in financial markets internationally, presenting a theoretical and practical issue referred to in finance academia as the 'closed-end fund puzzle'. In the field of financial economics there can be few questions more complicated than the closed-end fund puzzle, and it has been a subject of investigation for several decades (for an overview, see Anderson and Born, 1992). The puzzle is so-called because at IPO, in the US the average closed-end fund is issued at an almost 10 percent premium to the NAV, while in the UK funds are issued at a premium amounting to at least 5% (Weiss, 1989; Peavey, 1990). However, within a few months, averaging at around 120 days in

[5] NAV is defined as the market value of the securities held less liabilities, all divided by the number of shares outstanding.

recent years, the premium disappears, the fund trades at a discount, and during the closure period transactions retain this discount,[6] albeit that it is not fixed but varies substantially over time (Thompson, 1978). When the closed-end fund is either converted into an open-end fund or liquidated, the discount shrinks and the share price will rise (Brauer, 1984).

A number of past studies have attempted to solve the puzzle by rational explanations such as agency costs, illiquidity of assets and capital gains tax. The agency costs theory proposes that in order to maintain normal operation, funds incur some costs, which would make the market price of a closed-end fund less than the NAV (Boudreaux, 1973; Ross, 2002). However, Thompson (1978), Malkiel (1977) and Lee, Shleifer and Thaler (1991) find little support for this hypothesis, because agency costs are usually a fixed portion of the NAV and therefore should not impact the fund price. With regard to the illiquidity of assets, Seltzer (1989) suggests that because fund managers always invest large amounts of money into assets that are in restricted circulation, the market value of the assets exaggerates the real NAV; hence, there tends to be more discounting. However, this is inconsistent with the fact that when funds are open-ended, their price rises. Finally, in order to qualify for exemption from corporation tax a closed-end fund must distribute a certain percentage of realized gains. If funds have numerous unrealized gains, shareholders will be liable for capital gains tax, and therefore there would be a discount. However, contrary to this theory, Malkiel (1977) finds that unrealized capital gains can account for only a 6% discount, while evidence shows that the discount sometimes reaches 20%. Brickley, Manaster and Schallheim (1991) link an alternative tax-timing explanation to discounts on closed-end funds, based on the idea that investors of individual securities derive greater benefits from tax-timing than do fund

[6] Gemmill and Thomas (2000) find that the average discount in the UK over 1970-99 is 18%, and in the US over 1973-99 it is 14%.

shareholders, because current tax law prohibits the capital losses of individual assets from being passed through to investors of the portfolio. Nevertheless, their study fails to provide conclusive evidence that tax-timing can impact on closed-end fund discounts, nor can it explain why funds trade at a premium.[7] Therefore, while these theories can offer some insights towards explaining the discount puzzle, none of them provides a satisfactory explanation for all aspects of the puzzle, because each fails to account for a great deal of the existing evidence.[8]

Investor sentiment hypothesis, proposed in the US by Lee, Shleifer and Thaler (1991) (LST henceforth), involves a simple behavioural approach using models in which not all the investors are fully rational. Although the concept of investor sentiment remains controversial, it is a developing perspective to the study of financial markets that has emerged, at least in part, in response to the perplexing problems encountered by the classical theories. As such, it has taken its place on the cutting edge of finance studies. The investor sentiment theory has been reliably tested (LST, 1991; Chen et al, 1993; Barberis, 2002; Baker and Wurgler 2007), and the empirical findings demonstrate that investor sentiment plays a key role in evaluating the discount of closed-end fund. Many researchers have confirmed that a relationship exists between the closed-end fund discount puzzle and investor sentiment, and it has been argued that discount is a sentiment index. However, other studies and empirical evidence have indicated that investor sentiment seems to account for very little of the discount on closed-end funds over time (Elton et al, 1998; Ross, 2002; Doukas and Milonas, 2004).

Behavioural explanations are currently providing new insights in the world of finance research, as they attempt to explain existing puzzles in the literature. The outcome of my

[7] See, for example, Constantinides (1983, 1984) and Kim (1994).
[8] See Roenfeld and Tuttle (1973), Malkiel (1977), Brauer (1984), Brickly and Schallheim (1985).

research opens up potential opportunities for exploiting the relationship between discounts and investor sentiment. Understanding the underlying mechanisms and influential factors of the closed-end fund discount can guide fund managers in their management and investment decisions. By undertaking this kind of closed-end fund research, it will be possible to offer better advice to investors regarding fund and stock markets, so that they can make better informed decisions and so reduce their investment risk. Moreover, the analysis of closed-end fund discounts will not only help guide management and investment decisions, but since the impact of closed-end fund discounts involves the same factors as those related to the open-end fund redemption pressure, it will also have great significance for the management of open-end fund liquidity.

With these considerations in mind, we begin by analyzing the theoretical foundations and empirical findings of existing research on this issue. To this end, we review the main studies which either support or sharply challenge the investor sentiment theory. We draw on studies not only from the US and UK, but also from the rest of the world.

2.2 Literature Reviews

Zweig (1973) was the first to suggest that discounts on closed-end funds reflect the expectations of individual investors. To support his hypothesis, he developed a test model which uses the change in closed-end fund premiums as an index of shifts in investor expectations. In his empirical work based on the Dow Jones Industrial Average (DJIA) from December 1965 to January 1971, he found that investor expectations shown to be significant to related to the closed-end fund discount. This finding should be deemed the origin of investor sentiment theory. According to Black (1986), investors usually trade based on information, and are rational. However, sometimes they trade without information, and as a result they are incorrect and irrational; these behaviours lead to noise trading, which is essential in liquid markets.[9]

De long, Shleifer, Summers and Waldmann (1990) (DSSW henceforth), present a model of noise trader survival in perfectly competitive market conditions, which can be applied to the discount of closed-end funds. Sometimes, noise traders are optimistic on their trading assets and enhance prices; at other times, noise traders are pessimistic about the returns on securities, so the prices are driven down and closed-end funds sell at a relatively larger discount. Further, the authors assume that noise traders' sentiment is stochastic and the risk of holding a closed-end fund includes not only the fund's portfolio risk but also the risk from noise traders' sentiment on the fund changes. That is why Palomino (1996) suggests that the noise trading may explain the closed-end fund puzzle.

LST (1991) build on the investor sentiment theory based on DSSW's (1990) noise trading model. They point out that if investor sentiment changes, there are a number of empirical implications for the pricing of closed-end funds, most significantly because the risk of fund investment is systematic and holding the funds is riskier than holding their portfolios directly. Consequently, investors require higher returns on the assets of funds than on the same assets traded directly. This theory can explain why, in order to lead investors to purchase the funds, the closed-end funds must sell at a discount to the NAV. Further, the authors imply that the changes in investor sentiment on future returns may cause the fluctuations of the closed-end

[9] Black (1986) launched the 'noise' concept in a paper entitled 'Noise'. He stated: 'In my model of the way we observe the world, noise is what makes our observations imperfect.'

fund discount.

However, the considerable body of theoretical literature generated since investor sentiment theory was first proposed is by no means unanimous in terms of findings. Investor sentiment theory has been sharply challenged, especially by studies testing mainly the US or UK market. Among US studies, Chen, Kan and Miller (1993) question the link between discounts and premiums on small firm returns, because the data show that the returns of small capitalization stocks are not so strongly related to closed-end fund discount, and the relationship between them is not substantially stronger than that of larger capitalization stocks. Pontiff (1997) uses the same sample as LST (1991) and finds that the monthly returns of US closed-end funds are 64% more volatile than their assets. Moreover, the test for the difference in residual risk between top and bottom groups indicates that the discount is positively related to the residual risk; that is, the higher the residual risk, the higher is the absolute value of the discount, and vice versa.

Among UK studies, Prior (1995) disputes investor sentiment theory and concludes that the existence of the discount does not itself reflect the noise trading in the pricing of closed-end funds. This is because, if noise is found, it is likely to be in the patterns of positive short-run correlation with the sector mean; however, these patterns are actually long-run, hence the explanations in terms of investor sentiment cannot be successful. More recently, Gemmill and Thomas (2002) use a large sample of 158 closed-end funds to make cross-sectional tests of the factors determining the average discount. Their results indicate that investor sentiment can cause the fluctuation in the discounts; nevertheless, they reject the hypothesis that investor sentiment leads to the long-run discount.

The above studies do challenge the investor sentiment theory to some extent; however, many papers still support LST (1991) because many of the opposing hypotheses or models are either limited as regards the sample and the market, or not robust enough to disprove the investor sentiment theory. Therefore, much of the literature pays more attention to the specific measures of investor sentiment, which could provide more reasonable and compelling evidence. As a result there have been numerous studies, some supporting the investor sentiment theory and some challenging it, on the grounds of empirical findings.

2.2.1 New Issues (IPOs)

The first strand of the investor sentiment theory literature focuses on the closed-end fund IPO. LST (1991) examine closed-end fund issuing activity in the US, and find that issuing patterns are substantially cyclical. The issuing of closed-end funds tends to be crowded together at certain times; most funds are issued when the discounts on closed-end funds are much lower than normal. Consistent with the implication of investor sentiment theory, Burch and Weiss Hanley (1996) suggest that when timing secondary offerings, the closed-end fund managers are likely to choose those periods when funds are in high demand and are being traded at a premium. Further, Weiss Hanley, Lee and Seguin (1996) use the evidence of uninformed buyers to support investor sentiment. Testing on a sample of 65 closed-end fund IPOs issued during 1988 and 1989 on the NYSE (New York Stock Exchange) by applying the Lee-Ready (1991) algorithm, they find that most of the trading in the first few weeks is seller-initiated.[10] Their evidence shows that an extremely large number of the buys (sells) during the first 30 days are originated by small (large) investors. They explain that the closed-end funds are

[10] Weiss Hanley et al. (1996) interpret that since short-selling is impossible during this time period, this selling pressure confirms the presence of 'flippers' - investors who buy IPO shares during the pre-issue and immediately resell them in the aftermarket.

bought by uninformed buyers (irrational investors) from professionals; as a result, only small investors hold these funds over a long period, and this is why discount occurs.

However, Ammer (1990) argues that although the discount and premium periods of the UK closed-end funds are similar to those of the US, the irrational investor sentiment waves are not sufficiently significant to be a proxy of the emergence of discounts. Contrary to this, Levis and Thomas (1995) support the investor sentiment model and show that UK closed-end fund IPOs are subject to ‘hot’ issue periods; specifically, IPOs tend to occur when there is a marked narrowing in the discount of seasoned funds. In a subsequent study, Levis and Thomas (2000) show that IPOs in UK funds are usually launched when the discounts are at historically low levels. Moreover, their evidence indicates that individual investors tend to invest in UK mutual funds when the discounts are narrowing. Inconsistent with LST (1991), Khurshed and Mudambi (2002) propose an alternative approach to explain short-run underpricing of closed-end fund IPOs in terms of information asymmetry hypothesis. They use comprehensive UK closed-end fund IPO data of the period 1989-1996 to test the short-run fund price performance, and the results lead them to accept the hypothesis.

Recent work has focused on testing investor sentiment using the cross-section of stock return from closed-end fund IPOs. Baker and Wurgler (2006) construct a composite index of sentiment based on six underlying variables which are measured annually from 1962 to 2001. The regression result illustrates that the IPO market is essentially sensitive to investor sentiment, since the high first day returns on IPOs could be a measure of investor optimism, and the low returns could be interpreted as a reflection of market timing. Qiu and Welch (2005) provide a true out-of-sample test by forming their sample from 1985 to 2002. From their empirical evidence, they show that a consumer confidence measure can explain closed-end fund IPO activity, while the closed-end fund discount cannot; the sentiment is an important factor in financial markets, but not in explaining the discount. Unlike previous studies, which focus on the market prices to measure sentiment, Lemmon and Portniaguina (2006) rely on a direct measure of sentiment compiled from survey data, and construct a regression of consumer confidence on a set of macroeconomic variables. After comparing the sentiment which is extracted from consumer confidence indices to the discount of closed-end fund, the number of IPOs and the average first-day IPO return, they argue that the closed-end fund discounts appear to be not related to the investor sentiment.

2.2.2 Individual Investors

Behavioural explanations for the discount of closed-end funds focus on the behaviour of individual investors. Some of the individual investors who are the primary owners of closed-end funds are noise traders; sometimes they are too optimistic while at other times they are too pessimistic, and thus exhibit irrational swings in their expectations about future fund returns. Therefore, DSSW (1990) suggest that the risk of holding shares includes not only the fund's portfolio risk but also noise trader risk; hence the risk of holding fund shares is greater than the portfolio risk, and the discount is produced to compensate for the noise trader risk.

Sias et al. (2001) examine the DSSW (1990) hypothesis that closed-end fund shareholders obtain greater returns than holders of the underlying assets as compensation for bearing ‘noise trader risk’. Based on their result, they do not argue against the existence of noise traders in the market, because of the growth in closed-end fund IPO and negative aftermarket performance. Furthermore, the result is consistent with the noise trader model whereby closed-end fund share returns are more volatile and exhibit greater mean reversion than the underlying asset returns. However, they find no evidence that fund shareholders earn greater returns than the holders of underlying assets, so investors cannot be compensated for the noise trader risk.

Sias (1997a, 1997b) investigates the impacts of institutional investors on the closed-end fund market. In the first study (Sias, 1997a), contrary to Weiss (1989) and LST (1991), he finds that institutional investors do not play a minor role in the closed-end fund market.[11] He reports that while institutional ownership, on average, is less than 5 percent, institutional investors account for more than 32 percent of the total volume of his fund sample. Therefore, the proportional ownership is much less than the institutional investor activity in the closed-end fund market. His empirical finding is inconsistent with the hypothesis that the closed-end fund share discounts are driven mainly by the individual investors, and demonstrates that the variation in the net order imbalance due to institutional investors is as important as the one due to individuals in moving closed-end fund share prices and discounts.[12] In the second study (Sias, 1997b), he investigates whether individual and institutional investors respond differently to changes in market conditions. Closed-end funds are the medium used to test the hypothesis because closed-end fund shares (held primarily by individual investors) and the underlying assets (held primarily by institutional investors) are claimed to be the same stream of distributions. The empirical results indicate that individual investors are more responsive than institutional investors to changes in market conditions, and these changes in market conditions generally contribute a larger change in share prices than do the value of the underlying assets. The results support the argument proposed by DSSW (1990) that noise

[11] Weiss (1989) reports that institutional holdings account for less than 5% of closed-end fund IPOs versus 29% of the shares in a control sample of non-closed-end fund IPOs; LST report less than 7% for their sample versus under 27% for a sample of the smallest capitalization decile of NYSE firms.
[12] He assumes the weekly reporting of NAV minimizes information asymmetries in the market, and the order flow imbalance moves share prices.

trading can lead to a large divergence between market prices and fundamental values.

Grullon and Wang (2001) posit that institutional investors and individual investors can also differ in terms of their abilities to access and/or process relevant information about the assets in which they invest. According to this argument, institutional investors prefer to concentrate their investments in the underlying assets rather than in funds, so that they can take an informational advantage over individual investors. In order to examine the closed-end fund discount, the authors develop a multi-asset trading model which emphasizes both institutional ownership and information asymmetry. The model provides testable implications for the closed-end fund discount: specifically, that the discount is negatively related to the institutional ownership differential and, in particular, the discount is positively related to the quality of private information in the fund's underlying assets. In general the discount reflects a difference in risk perception between informed and uninformed traders.

2.2.3 Small Firm Effect

Another strand of investor sentiment hypothesis empirical research tests the small firm effect. LST (1991) conjecture that the smaller stocks are predominantly traded and held by individual investors, so the changes in their sentiment (the changes of discount) should be correlated with the returns on small capitalization stocks. They find that small stocks do well when discounts on closed-end funds narrow, and perform badly when discounts widen.[13] Furthermore, closed-end funds display a particular size-related January effect; that is, the return of common stock of closed-end funds during first month exceeds the average monthly

[13] As LST (1991) assert, this evidence is inconsistent with the unmeasured capital gains tax liability hypothesis of discounts.

return of last months, especially in small closed-end funds. Kumar and Lee (2006) confirm the small firm effect in investor sentiment theory. In order to test their view, they construct a multifactor model using a database of more than 1.85 million retail investor transactions from 1991 to 1996, as advanced by Barberis et al. (2005). Their empirical results show that retail investors concentrate their holdings and trading activities in small firms, lower priced firms, and lower institutional ownership firms, which indicates that investor sentiment shifts have incremental power to demonstrate return co-movements among small capitalization stocks. Therefore, they conclude that the closed-end fund discount is more likely to be influenced by smaller firms than by large firms. These findings are also consistent with Daniel, Hirshleifer and Subrahmanyam (2001), in whose model the proxies for mispricing are market excess return (RMRF), the size factor (SMB), the book-to-market (HML), the momentum factor (UMD).

However, the small firm effect, whereby small stocks perform better than large stocks when the discounts narrow has been debated ever since it was argued by LST (1991). Chen, Kan and Miller (1993) reject the sentiment story because, measured correctly, the co-movement between fund discounts and small firm returns is neither strong nor sufficiently robust. In their regressions, they find that the coefficients of small firms are quite similar to those of firms with high capitalization; specifically, the relationship between the discounts and small firm returns disappears after 1975. In response, Chopra and LST (1993) point out that in fact, all small stocks are mainly held by individuals, so even ‘high’ institutional small stocks can be related to the discounts. Using much better data, they confirm that small stocks outperform large stocks while discounts are narrowing, shown by the fact that nine out of ten size deciles support their view.[14] The small firm effect based on investor sentiment has been further investigated by Swaminathan (1996) and Nagel (2005). Both authors' long horizon forecasting regressions demonstrate that the future excess returns on small firms can be predicted by closed-end fund discounts, and the additional tests indicate that the relationship between small firm expected returns and discounts emerges from positive covariance between their risk premiums.

Examining turn-of-the-year return and volume patterns for municipal bond closed-end funds, which are held mainly by tax-sensitive individual investors, Starks et al (2006) document a January effect for these funds, but not for their underlying assets, which gives support to LST's (1991) size-related January effect. They posit that this January effect can be explained by the tax-loss selling hypothesis: investors usually sell securities on which they have incurred losses before the year end, in order to lower their taxes on net capital gains. The intensified selling pressure depresses prices at year end, then prices rebound in January, resulting in large January returns. The differences in incentives for tax-loss selling between the holders of the closed-end funds and the holders of the underlying assets provide evidence to explain the discount and premium of the closed-end fund. However, the evidence in the UK market does not appear to support this hypothesis. Dimson and Minio-Paluello (2002) show that January returns are not higher than non-January returns throughout the period from January 1980 to March 1997. They also suggest that, on average, the discounts during January decrease, but the monthly changes of the discounts are not significantly different in January from those in other months. This phenomenon is explained in Dimson, Marsh and Staunton (2002), who point out that stock market patterns are often unable to migrate across

[14] Chen, Kan and Miller provide a further rejoinder to confirm their points and rebut LST (1991). See Chan, Kan, Miller, 'Yes, Discounts on Closed-End Funds Are a Sentiment Index: a rejoinder', *Journal of Finance*, 48, pp.809-810

the Atlantic, hence the UK closed-end fund discount tends not to be characterized by January effect, unlike that in the US market.

2.2.4 Co-movements

One of the implications in investor sentiment theory is that the fluctuations of discounts should be highly correlated across funds. Since the discounts of funds and other securities are affected by the same sentiment, changes in this sentiment should cause changes in discounts. LST (1991) use US domestic stock funds over the 1965–1985 period to show that the average pairwise correlation of annual changes in discounts among domestic stock funds is 0.389, while that of monthly changes is 0.248, which gives further support to their theory that discounts of different domestic funds tend to move together. Similarly, Minio-Paluello (1998) designs a co-integration analysis, which is a more robust specification of co-movements in discount than pairwise correlation. She finds that in the UK market, the average correlation of the changes in the discount of all pairs of funds in the 'International general' category is 0.3, which shows that the fund discounts in that category co-move strongly. Moreover, she documents that the average discounts in different categories are co-integrated.

Barberis, Shleifer and Wurgler (2005) investigate why certain groups of assets co-move while others do not. They consider two broad theories of co-movement. One traditional view, derived from the concept that there is no friction and that investors are rational, holds that co-movement in prices reflects co-movement in fundamental values, while a more novel and currently prevalent view is a sentiment-based theory of co-movement, which believes that irrational investors exist, and that due to the limits to arbitrage, co-movement in prices is delinked from co-movement in fundamentals.[15] The authors use additions to the S&P 500 to construct a bivariate regression test to distinguish the two broad theories of co-movement, and find that the fundamentals-based view of co-movement cannot easily explain their results, but the sentiment-based view fits the evidence well. This is consistent with Vijh's (1994) US market findings and with Greenwood and Sosner (2002), who use data on additions to and deletions from the Nikkei 225 index.

As argued by LST (1991), the fluctuations in the discounts on closed-end funds are related to changes in the sentiment of individual investors, and changes in closed-end fund discounts are correlated with the returns of small-cap stocks. Scruggs (2007) supports this view and suggests that changes in closed-end fund discounts are analogous to the returns on a portfolio; that is, long on the common stocks of closed-end fund and short on the underlying assets. He uses the habitat view of co-movement to indicate that changes in the sentiment of individual investors relative to the sentiment of the broader market cause fluctuations in the discounts on closed-end funds. His empirical evidence, which is consistent with LST's (1991) limited arbitrage-noise trader model, shows that correlations between long-short portfolio returns and country-specific index returns are due to co-movement in noise shocks, not co-movement in fundamental shocks. Overall, the predictions of sentiment-based theories of co-movement add to the conviction of investor sentiment theory for valuation.

However, Chan et al. (2008) claim that while the explanations based on investor sentiment

15 They examine three specific sentiment-based views of co-movement. 1.Category View: to simplify portfolio decisions, many investors first group assets into categories then allocate funds at the level of these categories. If some of them are noise traders with correlated sentiment, then as they move funds from one category to another, their coordinated demand induces common factors in the returns of assets that happen to be classified into the same category. 2.Habitat View: noise traders only invest in a subset of available securities; their noise trading induces sentiment-based co-movement in the returns of stocks in that habitat. 3.Information Diffusion View: due to market friction, information is incorporated more quickly into the prices of some stocks than others; some stocks reflect it today and move up together immediately; the remaining stocks also move up together, but only after some delay.

hypothesis have had some success in accounting for the co-movement of fund premia or discount, they do not explain the wide variation of such premia or discount. In their reports of US-traded single-country closed-end funds, according to the average values (across all funds) of the time series correlations of the variables used in the empirical analysis, there is a strong co-movement in the premia of different funds, as suggested by the correlation of 0.47 between the individual and average fund premium, which is the proxy of small investor sentiment. They also find a strong co-movement among all country funds, but they suggest that it is not clear whether the co-movement necessarily reflects small investor sentiment.

2.2.5 Investor Sentiment in Different Markets

As noted by Elton et al. (1998), investor sentiment is priced in the US capital market, and as such it cannot be ruled out that it is limited to the US capital market. Investor sentiment theory cannot be sufficiently robust without being tested in capital markets outside the US. With this in mind, the final strand of empirical work tests the relationship between discount of closed-end funds and investor sentiment theory based on various capital markets. Simpson and Ramchander (2002) employ a novel approach to re-test the investor sentiment hypothesis for the Australia closed-end funds. Their evidence shows that after controlling for the movements between domestic and foreign stock market, as well as exchange rate, the changes of proportion between domestic and foreign investor sentiment are statistically significant to explain the changes in the discount of Australia closed-end funds. Jackson (2003) provides additional evidence to examine LST’s (1991) conjecture by studying systematic trading patterns in the Australian stock market. The findings offer supportive evidence for the small firm effect in Australia closed-end funds; however, the argument that individual investors are irrational and that this may result in the discount of closed-end funds is not valid.

Chowdhury (1994) compares different investor structures for closed-end funds in the US stock market and in Asian markets (Hong Kong, Korea, Singapore and Taiwan), and questions the general hypothesis that changes of closed-end fund discount seem to be related to announcement of changes in investment restrictions. His findings indicate that investor sentiment hypothesis is sensitive to the nature of the capital market. In the same vein, Chen et al. (2002) assert that due to the unique characteristics of the Chinese stock market, not only investor sentiment, but also imperfect arbitrage and the momentum effect play major roles in discounts of Chinese closed-end funds.

Doukas and Milonas (2004) conduct an out-of-sample test of the investor sentiment hypothesis and suggest if the sentiment can represent a systematic asset pricing risk and enter the return generating process, it should be found in the Greek market, which is more reactive to investor sentiment than is the US stock market.[16] However, the result fails to support the investor sentiment hypothesis. Using the same data and also testing in the Greek market, Halkos and Krintas (2006) find that the closed-end fund discount can be explained not only by the compensation for investor sentiment risk, which is consistent with LST (1991), but also by the efficient market hypothesis (EMH). In their model, fundamental factors have a significant relation and a slightly greater influence than behavioural factors on the growth of the discount of the closed-end funds, consistent with the arguments of researchers who rely on EMH as the answer to the closed-end fund discount puzzle.

[16] They argue that the Greek capital market is not as mature as the US capital market, hence individual investors' trading can be easily impacted by others, and consequently, investor sentiment is more likely to be detected.

The studies of investor sentiment on different markets extend even to Latin America. Garay and Venezuela (2001) provide an event study on the performance of closed-end funds in Latin America after the Asian Financial Crisis. They verify empirically that during the Asian Financial Crisis of 1997-1998, following the currency devaluations the closed-end funds moved to large premiums. This fact makes powerless all the existing theories that attempt to explain the closed-end fund discount puzzle.

2.3 Methodology and Data

2.3.1 The Out-of-sample Test

The results in the study of LST (1991) may be limited, due to the fact that the hypothesis of investor sentiment is based solely on the US market. That is, since investor sentiment is sampled only in the US capital market, it cannot be ruled out that the result is limited to that market. For example, by testing the investment decision rules, Draper and Paudyal (1991) find that the UK investment trust market, unlike the closed-end fund market in the US, is efficient. Our methodology is designed to investigate the investor sentiment theory by using out-of-sample test based on the UK market and different sample periods. As discussed, investor sentiment varies across different countries, each of which has its own unique corporate governance, financial system and capital structure. In this respect, Fama (1998), in his response to the many critics who oppose the idea of the rationality of capital markets, provided instruction on how to deal with out-of-sample tests, because most capital market anomalies, such as closed-end fund discounts, tend to disappear in other markets or after the publication of the original papers. The out-of-sample test therefore seems applicable to unveiling the relationship between the closed-end fund discount puzzle and investor sentiment.

However, previous models of the discount have been limited to using a small number of domestic equity market factors, notably the market sector factors. These risk factors have limited explanatory power, and additional factors are required to explain a substantial proportion of movements in the discount and the portfolio returns. We consider four such factors: the market, small firm, market-to-book, and momentum factors. This research uses time series models, because the closed-end fund discount puzzle is considered as a time series performance, and it is therefore necessary to use time-series sentiment evidence to test for it. If sentiment does play a systematic role in explaining the time series of stock returns, a time-series regression on the different variables should essentially confirm the significance of investor sentiment to the closed-end fund market. We consider Pontiff's (1997) empirical attempt to take into account the Fama and French (1993) three factor model and the models developed by Carhart (1997), as the first step toward shedding light on and improving understanding of this issue.

2.3.2 Data Sources and Descriptions

Using the UK data from January 1990 to December 2008, we aim to shed more light on whether or not investor sentiment is related to the discounts of closed-end funds, and whether it could be incorporated in asset pricing. The selection of the UK closed-end funds is based on several reasons. First, as shown in Figure 1, we may find that the UK stock market experienced both a valley and a peak during the 1990-2000 periods. The bearish market lasted until the beginning of 2003, while the unprecedented bullish trend prevailed from 2002 to 2008 and the last really high peak occurred in 2007. After 2008, the stock market became very unstable and experienced valleys again. The market has not yet regained its 1990 low value; it seems to be recovering slowly, but steadily. During the first period, the London Stock Exchange index (FTSE100) rose from about 2000 to more than 6000, while by July 2007 it had reached 6700 points and after that fell to 4000. In such a stock market environment investors experienced both optimism and pessimism; hence the investor sentiment should be more noticeable.

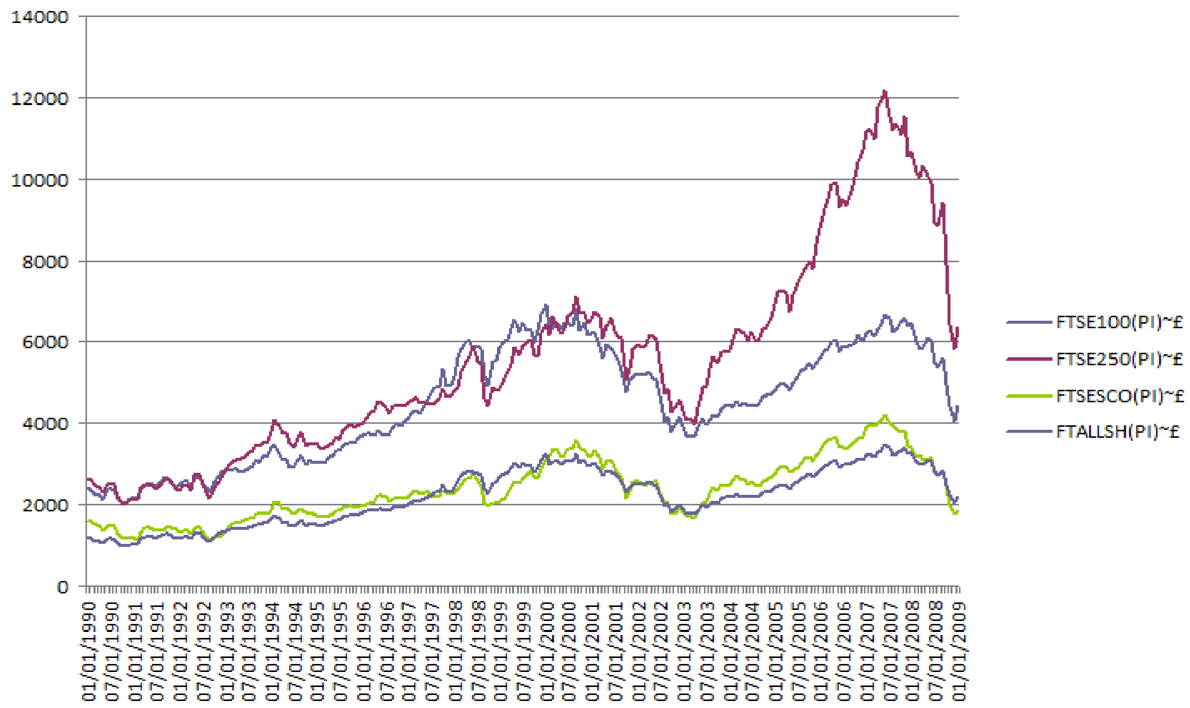


Figure 2.1 Stock indices over time during 1/1990–1/2009 (Data source: DataStream).

Second, the UK and US stock markets are the most sophisticated and developed in the world, and their capital structures are very similar. Consequently, if there is a relationship between closed-end fund discount and investor sentiment, the indications in the UK should be the same as in the US, and investor sentiment should have similar impact on the investment decision and asset pricing in the two markets. Third, investor sentiment hypothesis demonstrates that the closed-end fund discount is caused mainly by small investors. As the statistical evidence shows, in both the UK and the US the percentage of small investors is too low for them to play a bigger role than that of institutional investors. Institutional investors are much more significant in the UK market than in any other markets, including other developed countries. Their wealth represents around two thirds of the total equity in public listed companies.[17] If we find that investor sentiment plays a key role in the closed-end fund discount in a country where institutional investors take the dominant place in the capital market that will be strongly persuasive evidence for investor sentiment theory.

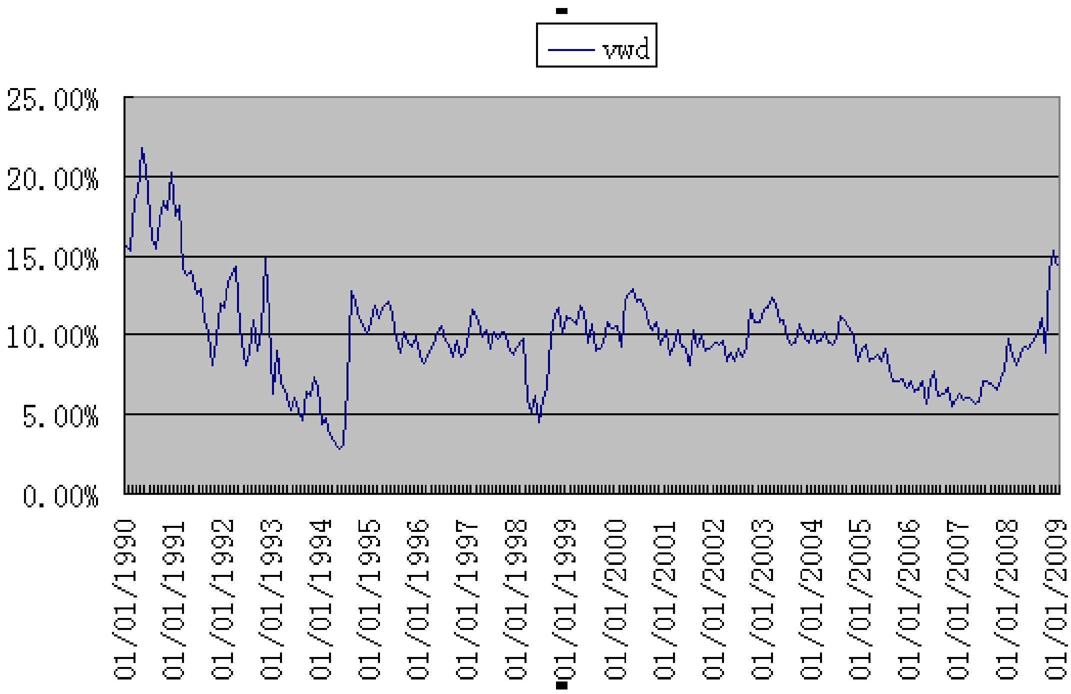


Figure 2.2 Value-weighted discount for all closed-end funds listed in the LSE over the period of 01/1990-01/2009

Finally, from Figure 2 we can find the most important and interesting factor in our sample; that is, almost all of the closed-end funds were trading at a discount during the 1990-2009 periods, as shown by the fact that the value-weighted percentage of discounts is above zero. Therefore, the UK market provides us with a distinct opportunity to study the relationship between investor sentiment and the closed-end fund discount puzzle in a context where it is

[17] The main types of institutional investor are insurance companies, pension funds, hedge funds, closed-end funds and mutual funds.

more easily to be observed. If we are unable to find sufficient evidence to support the investor sentiment hypothesis, we may argue that investor sentiment is not a key factor in asset pricing.

We employ monthly data spanning the period from January 1990 to December 2008; since previous findings are widely divergent, we restrict our sample to the post-1990 period to enable the data to be as new as possible. The sample consists of 86 closed-end funds listed in the London Stock Exchange. Although 98 closed-end funds were initially identified in Datastream during this period, 12 either have missing data through this source, or do not provide share information. We use the FTSE 100 index, FTSE 250 index, and FTSE Small Cap index as the portfolio indices. Our data related to the closed-end funds, sector indices and individual stocks are collected from Datastream. All other data are obtained from the Xfi Centre for Finance and Investment. As Michou, Mouselli and Stark (2007) note, there is no freely downloadable equivalent to the data on Ken French's US website; however, Gregory, Tharyan and Huang (2009) remedy this situation by making available the Fama-French and Momentum portfolios and factors for the UK market to the wide community of UK academic and post-graduate researchers.

2.3.3 Portfolios and Indices

Following Doukas and Milonas (2004), who use out of sample test methodology and LST (1991), we test the argument that investor sentiment plays a key role in the return generating process by constructing several sets of portfolios.[18] First, we derive 3 value-weighted portfolios from the FTSE indices, which are classified by capitalization. The FTSE 100 is a share index of the 100 most highly capitalized UK companies listed on the London Stock Exchange; this is followed by the FTSE 250 and FTSE Small Cap indices. Second, we adopt a more concise 10 size-decile portfolio from Gregory, Tharyan and Huang (2009), which is consistent with the study of LST (1991). We also use 10 FTSE sector indices to test the industrial returns. Finally, 383 individual stocks are taken into our portfolios; these are the remaining stocks of the original 419 listed in the LSE during my sample period, after the exclusion of 36 with missing data. Then, we evaluate equally-weighted monthly returns for each of these portfolios within the sample period.

Taking the previous studies into account, we construct the investor sentiment index by using the value-weighted index of discounts. The process is shown as follows:

$$VWD_t = \sum_{i=1}^{n} w_i DISC_{it}$$

Where,

$$w_i = \frac{NAV_{it}}{\sum_{i=1}^{n} NAV_{it}} \qquad (2.1)$$

NAV_{it} = net asset value of fund at end of month t

[18] LST (1991) built the changes in the discount on closed-end funds as the sentiment index. Chen, Kan and Miller (1993), and Elton et al. (1998) also use the changes in value-weighted discount as the sentiment index.

$$DISC_{it} = \frac{NAV_{it} - SP_{it}}{NAV_{it}} \times 100 \qquad (2.2)$$

Where, SP_{it} = stock price of fund I at end of month t

n= the number of funds with available discount and NAV data at the end of month t.

We also compute the changes in the value-weighted index of discounts, defined as:

$$\Delta VWD_t = VWD_t - VWD_{t-1} \qquad (2.3)$$

2.3.4 The Return Generating Process

In order to test the importance of adding sentiment index to the return generating process, we use two different models to test LST's (1991) investor sentiment hypothesis that investors should require higher returns to compensate their small investor sentiment risk. If this hypothesis is valid, the sentiment factor should have a significant coefficient when it gets into the return generating process and the average alpha should be different from zero. First, as Doukas and Milonas (2004) use an improved model based on LST's (1991) one-index model to examine the relationship between returns against market returns and ΔVWD, we employ the following similar model:

$$R_{it} = \alpha_i + \beta_{im} R_{mt} + \beta_{i0} \Delta VWD_t + \varepsilon_{it} \qquad (2.4)$$

Where,

R_{it} = the return of a stock or portfolio i in month t minus the one-month London Inter Bank Offered Rate (LIBOR)

R_{mt} = the return of market portfolio m in month t minus the one-month LIBOR

ΔVWD_t = the change in value-weighted index of discount in month t

α_i = the non-systematic mean return of stock or portfolio i

β_{im} = the sensitivity of stock or portfolio i to market portfolio m

β_{i0} = the sensitivity of stock or portfolio i to the index of changes of premiums

ε_{it} = the residual of stock or portfolio i in period t

However, many studies remain unconvinced that model (4) is an appropriate return generating process; a more precise model should add the Fama-French three factors of market, size, and book-to-market, as well as the momentum factor.[19] Therefore, the second model is designed to test the relationship between the sentiment in the return generating process and Carhart's (1997) four-factor model, which adds the momentum factor to the three-factor model. The model can be presented as:

[19] See L'Her, Masmoudi and Suret (2004) for the Canada stock market.

$$R_{it} = \alpha_i + b_i R_{mt} + s_i SMB_t + h_i HML_t + w_i WHL_t + \beta_i \Delta VWD_t + \varepsilon_{it} \qquad (2.5)$$

Where,

SMB= the return on a portfolio of small stocks minus the return on a portfolio of big stocks (small minus big in terms of size)

HML= the return on a portfolio of value stocks minus the return on a portfolio of growth stocks (high minus low in terms of B/M)

WML= the return on a portfolio of winner stocks minus the return on a portfolio of loser stocks (winners minus losers in terms of momentum)

Moreover, we compute another sentiment proxy which is the survey based direct approach as the change of consumer confidence index ΔCCI. GFK NOP have been conducting the Consumer Confidence Barometer in the UK since June 1995. Each month the survey tracks changes in personal finance, general economic situation, inflation, unemployment, current purchasing climate, consumer spending and saving. We estimate the components of consumer confidence related to economic fundamentals and investor sentiment. This approach would be better than the traditionally indirect way to construct the sentiment proxy as it is easy to be captured and can be calculated more accurately. We compare the two different approaches for the sentiment proxy in order to test the robustness of the results.

2.4 Empirical Results

2.4.1 Characteristics of the Sample

Table 2.1 shows the descriptive statistic of our sample. It reports that almost all the closed-end funds were trading at a discount to their NAV, 83 out of 86 closed-end funds, with a mean discount of around 12.05%. This table also illustrates that during our sample period, i.e. January 1990 to December 2008, the closed-end funds performed better than the UK stock market by about 0.284%. Furthermore, it reports the NAV returns of our sample. Given that these have a mean return of around 0.276%, it is clear that the closed-end fund returns outperform the NAV returns. This result would seem to support LST's (1991) argument that closed-end funds should offer a higher (lower) return to compensate investors for the sentiment risk when a discount (premium) is introduced, since UK closed-end funds are being traded at a discount, but returns are higher than NAV returns,[20] albeit not very significantly.

Table 2.1 Closed-end Fund descriptive statistics

	Obs.(No.)	Mean(%)	Value>0(No.)
Discounts	228	12.05	83
Returns	227	0.284	70
NAV returns	227	0.276	72

Notes: Table 2.1 reports the monthly average discounts, returns and NAV returns of 86 closed-end funds in our sample period from January 1990-December 2008.

[20] See also Elton et al. (1998), who use an equation based on Return of Fund= Return of NAV+ Dividend*Discount/Price to support the argument by LST (1991).

2.4.2 Co-movements in Discounts of Closed-end Funds

The investor sentiment hypothesis predicts that the discounts on closed-end funds will be correlated. Table 2.2 presents the correlation levels of monthly discounts of individual funds and the value-weighted discount (VWD) of all 86 closed-end funds from our sample. The fact that correlation coefficients are not too far from 1 and -1 indicates that most of the discounts of funds are correlated well. In addition, the correlation between VWD and each discount of individual closed-end funds is fairly strong; the average pairwise correlation of all funds and VWD is 0.28. This figure is close to the correlation reported in LST (1991) to support their conclusion that there is co-movement between the discounts of each individual closed-end fund.

Table 2.2 Fund correlation levels

CF1	CF2	CF3	CF4	CF5	CF6	CF7	CF8	CF9	CF10	CF11
0.2320	0.2483	0.5718	0.3251	0.3251	0.5202	0.3199	0.1769	0.3557	0.3424	0.0420
CF12	CF13	CF14	CF15	CF16	CF17	CF18	CF19	CF20	CF21	CF22
0.3163	-0.4631	0.1531	-0.2692	0.5876	0.2141	0.0451	0.1540	-0.1361	0.2605	0.4286
CF23	CF24	CF25	CF26	CF27	CF28	CF29	CF30	CF31	CF32	CF33
0.3514	0.4329	0.1440	0.3374	-0.2426	0.5544	0.2368	0.1420	0.3349	0.2210	0.5173
CF34	CF35	CF36	CF37	CF38	CF39	CF40	CF41	CF42	CF43	CF44
0.1130	-0.0013	0.4138	0.2351	0.3608	-0.0070	0.1615	0.0598	0.1037	0.4085	0.4386
CF45	CF46	CF47	CF48	CF49	CF50	CF51	CF52	CF53	CF54	CF55
0.3068	0.4578	-0.0358	0.3309	0.3555	0.4236	0.3018	0.1732	0.2214	0.4052	0.0940
CF56	CF57	CF58	CF59	CF60	CF61	CF62	CF63	CF64	CF65	CF66
0.2571	0.5432	0.3464	0.4153	0.2857	0.0487	0.2763	0.1003	0.3320	0.3232	0.5095
CF67	CF68	CF69	CF70	CF71	CF72	CF73	CF74	CF75	CF76	CF77
0.2026	0.3801	0.6018	0.7499	0.1539	0.3639	0.4161	0.3367	0.2901	0.2380	0.4406
CF78	CF79	CF80	CF81	CF82	CF83	CF84	CF85	CF86		
0.4949	-0.0748	0.3118	0.2412	0.5909	0.3248	0.2482	0.5561	0.3920		

Notes: This table presents the correlation levels of monthly discounts of individual funds and the value-weighted discount (VWD) of all 86 closed-end funds from our sample.

2.4.3 The Significance of Sentiment

In LST's (1991) theory, the main traders and holders of small stocks are individual investors, so if their sentiment changes, both small stocks and closed-end funds should be influenced. Table 2.3 reports the results of time series regression for our models. There are three parameters to be estimated in model 1, and six in model 2, to which have been added the Carhart (1997) four factors. The interesting finding here regards the significance of the parameter α, which defines the non-systematic mean return of portfolios. We obtain that the alphas of both models are statistically insignificant in all three portfolios. Moreover, identical to LST's (1991) finding, all three ΔVWD are significant at 5% level,[21] in the first model as well as in the ΔCCI model.

However, in contrast, the second model's regression demonstrates that not all of the coefficients of ΔVWD (ΔCCI) are significant at 5% level; the coefficients of ΔVWD for the FTSE 250 and FTSE Small Cap index are significant, but those for the FTSE 100 are not, which may indicate that the investor sentiment is more likely to be captured in small stocks. Furthermore, all of the size factors are significant, and consequently we may conclude that size enters the return generating process much more than do the market, B/M and momentum factors. The market betas are insignificant continuously in all regressions, while the alphas are relatively lower in regressions of model 2 than in regression model 1. From the values of adjusted R^2, we find that the Small Cap has the highest value; furthermore, since all the values of the adjusted R^2 are much higher in model 2 than in model 1, we can see that model 1 is able to explain a relatively small proportion of the variability of the excess returns on the market indices, and model 2 appears to be a rather better model.

[21] In order to be consistent with previous studies, we test the coefficients only at 5% level.

Table 2.3, Panel A

The time-series regression results with commonly used stock market indices

	Intercept	Market	ΔVWD	Size	B/M	Momentum	Adj.R^2
Model 1: $R_{it} = \alpha_i + \beta_{im} R_{mt} + \beta_{i0} \Delta VWD_t + \varepsilon_{it}$							
FTSE 100	-0.003	0.132*	-0.005*				0.031
	(-1.01)	(1.96)	(-2.23)				
FTSE 250	-0.002	0.153	-0.011*				0.083
	(-0.512)	(1.90)	(-4.40)				
FTSE Small-cap	-0.004	0.061	-0.013*				0.104
	(-1.34)	(0.750)	(-5.30)				
Model 2: $R_{it} = \alpha_i + b_i R_{mt} + s_i SMB_t + h_i HML_t + w_i WHL_t + \beta_i \Delta VWD_t + \varepsilon_{it}$							
FTSE 100	-0.002	0.092	-0.002	0.418*	-0.021	-0.012	0.113
	(-0.742)	(1.39)	(-1.07)	(4.85)	(-0.248)	(0.865)	
FTSE 250	-0.001	0.099	-0.007*	0.587*	0.070	0.012	0.194
	(-0.390)	(1.27)	(-3.08)	(5.82)	(0.694)	(0.148)	
FTSE Small-cap	-0.003	0.002	0.010*	0.589*	-0.030	-0.026	0.218
	(-1.02)	(0.028)	(-4.06)	(5.82)	(-0.293)	(-0.311)	

Notes: This table reports the time series relationship between monthly excess returns on three indices of FTSE, changes in the monthly discount on a value–weighted portfolio of closed–end fund discounts (VWD), and the monthly excess return on the FTSE All Shares, which is used as a proxy for the market return (Rmt). SMB is the portfolio of small stocks minus big in terms of size, HML is high minus low in terms of Book to Market, and WML is winner minus loser in terms of momentum. *denotes significant at 5% level.

Table 2.3, Panel B

The time-series regression results with commonly used stock market indices

	Intercept	Market	ΔCCI	Size	B/M	Momentum	Adj.R^2
Model 1: $R_{it} = \alpha_i + \beta_{im} R_{mt} + \beta_{i0} \Delta CCI + \varepsilon_{it}$							
FTSE 100	-0.003	0.094	-0.003*				0.061
	(-0.942)	(1.41)	(-3.62)				
FTSE 250	-0.001	0.095	-0.004*				0.070
	(-0.406)	(1.16)	(3.98)				
FTSE Small-cap	-0.004	0.009	-0.003*				0.033
	(-1.21)	(0.106)	(3.09)				
Model 2: $R_{it} = \alpha_i + \beta_i R_{mt} + s_i SMB_t + h_i HML + w_i WHL_t + \beta_i \Delta CCI + \varepsilon_{it}$							
FTSE 100	-0.002	0.073	-0.002*	0.380*	-0.044	-0.006	0.132
	(-0.706)	(1.11)	(2.41)	(4.42)	(-0.508)	(-0.0831)	
FTSE 250	-0.001	0.068	-0.002*	0.595*	0.058	0.034	0.181
	(-0.375)	(0.868)	(2.39)	(5.77)	(0.562)	(0.406)	
FTSE Small-cap	-0.003	-0.026	0.001	0.648*	-0.023	0.003	0.169
	(-1.01)	(-0.317)	(1.49)	(6.14)	(-0.218)	(0.031)	

Notes: This table reports the time series relationship between monthly excess returns on three indices of FTSE, changes in the monthly consumer confidence index, and the monthly excess return on the FTSE All Shares, which is used as a proxy for the market return (Rmt). SMB is the portfolio of small stocks minus big in terms of size, HML is high minus low in terms of Book to Market, and WML is winner minus loser in terms of momentum. *denotes significant at 5% level.

2.4.4 Sentiment and Size

In order to evaluate the contribution of a set of Carhart (1997) four factors to the return generating process, one major approach is to assess whether or not they impact on the size-sorted portfolios.[22] It is worthwhile to examine these because LST (1991) suggest that testing portfolios with different capitalizations of companies plays a key role in judging the investor sentiment hypothesis. Specifically, in their theory, small stocks held by individual investors are affected much more strongly than others. Therefore, small stocks are good candidates to be used for testing investor sentiment. The evidence based on size portfolios is presented in this subsection. To make a better comparison with prior studies, as discussed earlier, we use a more refined set of size-decile portfolios, ordered from smallest S1 to largest S10.

Table 2.4 reports the time series regression results of the monthly excess returns of each size portfolio on ΔVWD or ΔCCI and the market returns; the five-index regression results are also shown. As shown in Table 3(B), we find that in model 1, the values and patterns of adjusted R^2 are quite close to the finding of LST (1991) that the level of fit is much higher for large stocks (0.924) than for small stocks (0.323). Interestingly, almost all of the alphas are statistically insignificant and the average value of alphas is extremely close to zero; moreover, we find that all portfolios have the market beta close to 1. The t-value demonstrates that ΔVWD does have a significant relationship with the returns on size portfolios at 5% level in the first 9 regressions, but not in the last regression; this means that stocks do well when discounts narrow, and for decile 10, the largest firms, stock price does poorly when discounts shrink. The betas of changes in VWD are monotonic in portfolio size; the sensitivity of small

[22] Size portfolios are used as the unit of observation by Gibbons, Ross, and Shanken (1989), Fama and French (1992), Elton et al. (1998), and Doukas and Milonas (2004).

firms is much greater than that of large firms, because for the smallest firms, which typically have the highest individual ownership, the co-movement with closed-end funds is the greatest. All these findings are identical to investor sentiment hypothesis that sentiment index should be more pronounced in small stocks.

The regressions based on model 2 reveal that only one of the ΔVWD and only two of the ΔCCI have statistically significant coefficients. However, the patterns of regression coefficient on both ΔVWD and ΔCCI are different; specifically, there is no obvious sequence among the coefficients which relies on the size. Thus, if we take the Carhart (1997) four factors into account, the evidence fails to support LST's (1991) argument that large companies tend to have positive loadings, and small companies have negative loadings.[23] However, all of the coefficients of market and size and most of the B/M are significant. Moreover, the return of larger size-sorted portfolio is correlated to the momentum factor. From the adjusted R^2, we note that generally, the fit of model 2 is much better than that of model 1, especially for the smaller portfolios. Overall, we can estimate that in the UK market, there is a strong relationship between the Carhart (1997) four factors and the portfolio returns; specifically, the momentum factor is more prevalent in larger size portfolios than in other portfolios. Investor sentiment cannot be captured by adding the Carhart (1997) four factors.

[23] In LST's (1991) regression, the smaller the size-sorted portfolio is the greater absolute value of negative coefficient it has. This proves their hypothesis that small stocks do well when the discount narrows.

Table 2.4, Panel A

The time-series regression results using 10 size-decile portfolios

	Intercept	Market	ΔVWD	Size	B/M	Momentum	Adj.R^2
Model 1:	$R_{it} = \alpha_i + \beta_{im} R_{mt} + \beta_{i0} \Delta VWD_t + \varepsilon_{it}$						
S1(smallest)	0.008*	0.668*	-0.007*				0.323
	(2.72)	(10.1)	(-3.31)				
S2	0.005	0.795*	-0.006*				0.402
	(1.83)	(12.1)	(-3.08)				
S3	0.002	0.793*	-0.006*				0.412
	(0.649)	(12.3)	(-3.32)				
S4	0.001	0.859*	-0.006*				0.467
	(0.574)	(13.9)	(-3.29)				
S5	0.001	0.914*	-0.006*				0.521
	(0.306)	(15.5)	(-3.62)				
S6	0.001	0.973*	-0.007*				0.581
	(0.370)	(17.4)	(-4.44)				
S7	-0.001	1.004*	-0.006*				0.590
	(-0.327)	(17.8)	(-3.71)				
S8	-0.001	1.083*	-0.005*				0.689
	(-0.558)	(22.2)	(-3.63)				
S9	-0.001	1.188*	-0.002*				0.792
	(-0.512)	(29.4)	(-1.99)				
S10(largest)	-0.0002	0.921*	0.001				0.924
	(-0.238)	(52.3)	(1.51)				

Model 2:	$R_{it} = \alpha_i + b_i R_{mt} + s_i SMB_t + h_i HML_t + w_i WHL_t + \beta_i \Delta VWD_t + \varepsilon_{it}$						
S1(smallest)	0.007*	0.598*	-0.001	0.894*	0.161*	0.087	0.624
	(3.36)	(11.7)	(-0.848)	(13.5)	(2.42)	(1.60)	
S2	0.006*	0.693*	-0.0003	0.989*	0.188*	-0.018	0.748
	(3.16)	(15.8)	(-0.280)	(17.4)	(3.30)	(-0.391)	
S3	0.002	0.691*	-0.0004	1.036*	0.198*	0.001	0.798
	(1.49)	(17.8)	(-0.360)	(3.91)	(3.91)	(0.03)	
S4	0.003	0.762*	-0.0002	1.023*	0.073	0.003	0.832
	(1.69)	(21.30)	(-0.192)	(22.0)	(1.56)	(0.074)	
S5	0.002	0.823*	-0.0008	0.977*	0.124*	0.013	0.848
	(1.04)	(24.0)	(-0.731)	(21.9)	(2.78)	(0.362)	
S6	0.002	0.871*	-0.002*	0.954*	0.171*	-0.040	0.894
	(1.61)	(30.0)	(-2.31)	(25.3)	(4.50)	(-1.30)	
S7	0.001	0.894*	-0.0008	0.979*	0.275	-0.089*	0.912
	(1.19)	(33.5)	(-0.965)	(28.2)	(0.789)	(-3.12)	
S8	0.0006	0.989*	-0.0005	0.852*	0.038	-0.066*	0.935
	(0.565)	(43.3)	(-0.735)	(28.7)	(1.27)	(-2.71)	
S9	0.002	1.09*	0.005	0.559*	-0.020	-0.197*	0.920
	(1.76)	(42.3)	(0.628)	(16.6)	(-0.604)	(-7.09)	
S10 (Largest)	0.0004	0.929*	-0.0004	0.189*	-0.091*	-0.059*	0.948
	(0.736)	(61.9)	0.862	(-9.65)	(-4.62)	(-3.67)	

Notes: This table reports the time series relationship between monthly excess returns on ten size grouped portfolios, changes in value-weighted discount of CEF, and the monthly excess return on the FTSE All Shares, which is used as a proxy for the market return (Rmt). SMB is the portfolio of small stocks minus big in terms of size, HML is high minus low in terms of Book to Market, and WML is winner minus loser in terms of momentum. *denotes significant at 5% level.

Table 2.4, Panel B

The time-series regression results using 10 size-decile portfolios

	Intercept	Market	ΔCCI	Size	B/M	Momentum	Adj.R^2
Model 1:	$R_{it} = \alpha_i + \beta_{im} R_{mt} + \beta_{io} \Delta CCI + \varepsilon_{it}$						
S1(smallest)	0.008*	0.620*	0.003*				0.346
	(2.87)	(9.42)	(4.39)				
S2	0.005	0.749*	0.003*				0.424
	(1.97)	(11.6)	(4.30)				
S3	0.002	0.744*	0.004*				0.440
	(0.785)	(11.8)	(4.81)				
S4	0.002	0.820*	0.003*				0.472
	(0.669)	(13.2)	(3.64)				
S5	0.001	0.869*	0.003*				0.538
	(0.426)	(14.8)	(4.62)				
S6	0.001	0.925*	0.003*				0.593
	(0.506)	(16.6)	(5.21)				
S7	-0.0004	0.960*	0.003*				0.607
	(-0.212)	(17.3)	(4.88)				
S8	-0.001	1.052*	0.002*				0.690
	(-0.463)	(21.5)	(3.77)				
S9	-0.001	1.170*	-0.001*				0.796
	(-0.448)	(28.9)	(2.76)				
S10(largest)	-0.0002	0.927*	-0.004*				0.924
	(-0.289)	(52.4)	(-2.04)				

Model 2:	$R_{it}=\alpha_i+b_iR_{mt}+\beta_i\Delta CCI+s_iSMB_t+h_iHML_t+w_iWHL_t+\varepsilon_{it}$						
S1(smallest)	0.007*	0.588*	0.001*	0.874*	0.149*	0.091	0.627
	(3.41)	(11.5)	(1.73)	(13.1)	(2.24)	(1.68)	
S2	0.006*	0.688*	0.0005	0.976*	0.181*	-0.017	0.750
	(3.18)	(15.7)	(1.03)	(17.0)	(3.16)	(-0.371)	
S3	0.002	0.684*	0.0007	1.02*	0.188*	0.003	0.800
	(1.53)	(17.7)	(1.6)	(10.11)	(3.71)	(0.0622)	
S4	0.002	0.763*	-0.0005	1.028*	0.074	0.003	0.832
	(1.68)	(21.30)	(-0.138)	(22.0)	(1.58)	(0.091)	
S5	0.002	0.817*	0.0005	0.977*	0.118*	0.016	0.849
	(1.06)	(23.8)	(1.40)	(21.5)	(2.62)	(0.425)	
S6	0.002	0.861*	-0.007*	0.954*	0.166*	-0.034	0.894
	(1.62)	(29.5)	(2.09)	(24.9)	(4.33)	(-1.10)	
S7	0.001	0.888*	-0.0006	0.968*	0.021	-0.087*	0.914
	(1.23)	(33.3)	(1.86)	(27.7)	(0.596)	(-3.07)	
S8	0.0005	0.989*	-0.0001	0.863*	0.042	-0.065*	0.935
	(0.539)	(43.1)	(-0.525)	(28.7)	(1.38)	(-2.66)	
S9	0.002	1.098*	-0.0003	0.563*	-0.017	-0.199*	0.920
	(1.75)	(42.3)	(-0.937)	(16.6)	(-0.513)	(-7.18)	
S10 (Largest)	0.0004	0.928*	0.0001	0.188*	-0.091*	-0.058*	0.948
	(0.737)	(61.5)	(0.617)	(-9.50)	(-4.61)	(-3.61)	

Notes: This table reports the time series relationship between monthly excess returns on ten size grouped portfolios, changes in the monthly consumer confidence index, and the monthly excess return on the FTSE All Shares, which is used as a proxy for the market return (Rmt). SMB is the portfolio of small stocks minus big in terms of size, HML is high minus low in terms of Book to Market, and WML is winner minus loser in terms of momentum. *denotes significant at 5% level.

2.4.5 Sentiment and Sector Returns

According to LST (1991), the relationship between investor sentiment and closed-end fund discount puzzle also involves the ownership structure. Sentiment is supposed to be related to the firms with low institutional ownership, so we assume that the returns on different sectors will be affected differently by investor sentiment, based on the level of institutional ownership. Hence, an alternative way to test investor sentiment hypothesis is to specify whether the sentiment index can enter the return generating process of sectors with different institutional ownership, similar to small stocks. To test this conjecture, we replicate our earlier work to make an analysis on 10 sector indices.

Table 2.5 presents the time series regression results of the monthly excess returns of 10 sectors in LSE, ΔVWD or ΔCCI, and the monthly excess return on the market. From Table 4(B), we can see that for the two-factor model, 6 out of 10 of the ΔVWD betas are statistically significant at 5% level. This pattern is quite similar to our size portfolio regression, which means that the sensitivity of sector returns is very strong on the ΔVWD and ΔCCI. The sentiment seems to be strongly related to the return generating process in mutual funds. Regarding the alpha, this parameter defines the non-systematic mean returns of sector returns. We note that almost all the alphas are insignificant; their values are very close to zero, which is consistent with the results of LST's (1991) test. Furthermore, the goodness of fit for all regressions is strikingly low, with values lower than 0.1.

Now we focus on the regressions based on the second model, to which have been added three further risk factors. The regression results show that four coefficients of ΔVWD (five coefficients of ΔCCI) are statistically significant at 5% level in our sample. This is identical to the two-factor model, so that the relationship between the sentiment and sector returns is obvious. Interestingly, the pattern of alphas is also the same as in our two-factor model, with none being significant and all being close to zero. However, the adjusted R^2s are much higher than those in the two-factor model; thus, the explanatory power of these regressions is greater than those of model 1. Moreover, in our findings, different sector returns show substantially high sensitivity to the size factor; hence, both size and investor sentiment seem to be impacting on the sector returns.

In view of these results, our tests on different sectors can support the argument that investor sentiment plays a systematic role in the return generating process of portfolios of traded assets, which is consistent with LST (1991). Overall, the evidence presented in our models supports the view that sentiment originates from concentrated individual ownership.

Table 2.5, Panel A
The time-series regression results using 10 sector indices

	Intercept	Market	ΔVWD	Size	B/M	Momentum	Adj.R^2
Model 1:	$R_{it} = \alpha_i + \beta_{im} R_{mt} + \beta_{i0} \Delta VWD_t + \varepsilon_{it}$						
Oil & Gas	0.0002	-0.101	-0.001				-0.002
	(0.059)	(-1.12)	(-0.444)				
Basic Mats.	-0.003	0.158	-0.012*				0.052
	(-0.737)	(1.45)	(-3.56)				
Industrial	-0.005	0.159	-0.010*				0.055
	(-1.23)	(1.64)	(-3.59)				
Consumer Gds.	-0.002	-0.002	-0.009*				0.030
	(-0.556)	(-0.232)	(-3.02)				

Heath Care	-0.001	0.157*	0.0003	0.013
	(-0.503)	(2.27)	(0.137)	
Comsumer Svs.	-0.004	0.123	-0.01*	0.066
	(-1.31)	(1.54)	(-4.01)	
Telecom	-0.003	0.146	-0.004	0.009
	(-0.711)	(1.55)	(-1.38)	
Financials	-0.003	0.200*	-0.009*	0.055
	(0.429)	(2.20)	(-3.32)	
Utilities	0.002	0.058	-0.003	0.001
	(0.512)	(0.785)	(-1.40)	
Technology	-0.006	0.304	-0.011*	0.029
	(-0.892)	(-1.95)	(-2.34)	

Model 2: $$R_{it} = \alpha_i + b_i R_{mt} + s_i SMB_t + h_i HML_t + w_i WHL_t + \beta_i \Delta VWD_t + \varepsilon_{it}$$

Oil & Gas	-0.0004	-0.138	0.002	0.473*	0.195	0.062	0.059
	(-0.109)	(-1.54)	(0.605)	(4.04)	(1.65)	(0.646)	
Basic Mats.	-0.004	0.085	-0.006*	0.864*	0.372*	0.094	0.204
	(-0.999)	(0.833)	(-2.08)	(6.48)	(2.78)	(0.857)	
Industrial	-0.004	0.100	-0.006*	0.685*	-0.039	0.014	0.166
	(-1.02)	(1.07)	(-2.29)	(5.62)	(-0.322)	(0.140)	
Consumer Gds.	-0.003	-0.055	-0.006	0.627*	0.286*	0.075	0.117
	(-0.754)	(-0.540)	(-1.82)	(4.77)	(2.17)	(0.689)	
Heath Care	-0.0007	0.126	0.001	0.157	0.045	-0.068	0.021
	(-0.232)	(1.77)	(0.509)	(1.70)	(0.486)	(-0.894)	
Comsumer Svs.	-0.003	0.075	-0.007*	0.502*	-0.035	-0.014	0.150
	(-1.03)	(0.959)	(-2.86)	(4.91)	(-0.341)	(-0.171)	
Telecom	-0.0001	0.109	-0.002	0.409*	-0.429*	-0.072	0.114
	(-0.027)	(1.19)	(-0.626)	(3.44)	(-3.59)	(-0.737)	
Financials	-0.003	0.149	-0.006*	0.496*	0.179	0.007	0.110
	(-0.780)	(1.65)	(-2.26)	(4.22)	(1.52)	(0.0714)	
Utilities	0.002	0.032	-0.002	0.157	0.043	-0.045	0.002
	(0.650)	(0.422)	(-0.982)	(1.59)	(0.436)	(-0.559)	
Technology	-0.0003	0.236	-0.008	0.609*	-0.821*	-0.198	0.139
	(-0.0446)	(1.56)	(-1.73)	(3.10)	(-4.16)	(-1.22)	

Notes: This table reports the time series relationship between monthly excess returns on ten industrial sectors, changes in the monthly discount on a value–weighted portfolio of closed–end fund discounts (VWD), and the monthly excess return on the FTSE All Shares, which is used as a proxy for the market return (Rmt). SMB is the portfolio of small stocks minus big in terms of size, HML is high minus low in terms of Book to Market, and WML is winner minus loser in terms of momentum. *denotes significant at 5% level.

Table 2.5, Panel B

The time-series regression results using 10 sector indices

Model 1: $R_{it} = \alpha_i + \beta_{im} R_{mt} + \beta_{io} \Delta CCI + \varepsilon_{it}$

	Intercept	Market	ΔCCI	Size	B/M	Momentum	Adj.R^2
Oil & Gas	0.0004	-0.128	0.002*				-0.015
	(0.108)	(-1.41)	(2.05)				
Basic Mats.	-0.003	0.092	0.004				0.049
	(-0.648)	(0.841)	(3.44)				
Industrial	-0.005	0.092	0.005*				0.069
	(-1.14)	(0.950)	(4.06)				
Consumer Gds.	-0.002	-0.052	-0.003*				0.021
	(-0.556)	(-0.232)	(-3.02)				
Heath Care	-0.001	0.132	0.0022				0.046
	(-0.448)	(1.92)	(2.73)				
Comsumer Svs.	-0.004	0.065	0.004*				0.072
	(-1.21)	(0.811)	(4.21)				
Telecom	-0.003	0.123	0.002				0.009
	(-0.676)	(1.30)	(1.36)				
Financials	-0.003	0.200*	0.009*				0.066
	(-0.704)	(1.57)	(3.70)				
Utilities	0.002	0.028	0.002*				0.023
	(0.580)	(0.382)	(2.60)				
Technology	-0.006	0.264	-0.002				0.012
	(-0.851)	(1.67)	(1.18)				

Model 2: $R_{it} = \alpha_i + b_i R_{mt} + \beta_i \Delta CCI + s_i SMB_t + h_i HML_t + w_i WHL_t + \varepsilon_{it}$

	Intercept	Market	ΔCCI	Size	B/M	Momentum	Adj.R^2
Oil & Gas	-0.0002	-0.143	0.001	0.426*	0.176	0.057	0.060
	(-0.077)	(-1.58)	(0.849)	(3.60)	(1.48)	(0.596)	
Basic Mats.	-0.004	0.059	0.002*	0.875*	0.363*	0.114	0.197
	(-0.989)	(0.573)	(1.50)	(6.46)	(2.68)	(1.03)	
Industrial	-0.004	0.065	0.003*	0.659*	-0.066	0.033	0.173
	(-0.991)	(0.689)	(2.70)	(5.37)	(-0.537)	(0.335)	
Consumer Gds.	-0.003	-0.075	0.001	0.644*	0.282*	0.091	0.109
	(-0.751)	(-0.736)	(1.11)	(4.83)	(2.11)	(0.842)	
Heath Care	-0.0005	0.112	0.002	0.085	0.013	-0.072	0.042
	(-0.169)	(1.59)	(2.24)	(0.917)	(0.143)	(-0.953)	
Comsumer Svs.	-0.003	0.041	0.003*	0.488*	-0.057	0.006	0.152
	(-1.00)	(0.521)	(2.94)	(4.72)	(-0.550)	(0.069)	
Telecom	-0.0001	0.099	0.001	0.398*	-0.438*	-0.067	0.116

	(-0.015)	(1.07)	(0.867)	(3.30)	(-3.64)	(-0.688)	
Financials	-0.003	0.118	0.003*	0.483*	0.160	0.025	0.122
	(-0.758)	(1.30)	(2.34)	(4.06)	(1.35)	(0.262)	
Utilities	0.002	0.013	0.002*	0.122	0.022	-0.039	0.002
	(0.691)	(0.170)	(2.06)	(1.23)	(0.219)	(-0.483)	
Technology	-0.0003	0.212	0.001	0.653*	-0.817*	-0.175	0.130
	(-0.0536)	(1.39)	(0.727)	(3.27)	(-4.09)	(-1.08)	

Note: This table reports the time series relationship between monthly excess returns on ten industrial sectors, changes in the consumer confidence index (CCI), and the monthly excess return on the FTSE All Shares, which is used as a proxy for the market return (Rmt). SMB is the portfolio of small stocks minus big in terms of size, HML is high minus low in terms of Book to Market, and WML is winner minus loser in terms of momentum. *denotes significant at 5% level.

2.4.6 Sentiment and Individual Stock Returns

According to LST (1991), investors need a higher return due to the small investor sentiment, thus, compensate the sentiment risk. If sentiment does exhibit systematic effect on explaining the return generating process, we could observe that the ΔVWD and ΔCCI have significant loadings in individual stock returns. So we turn our focus on the relationship between monthly excess returns on 383 individual industrial stocks, ΔVWD (ΔCCI) and monthly excess return on the market, and B/M, size, momentum factors as well. From table 8, using the regression result of two-index model, we detect that the sensitivity of individual stock returns to our sentiment index ΔVWD (ΔCCI) is strong, because one third of the betas is significant at 5% level in all 383 regressions.

In the second model, the explanatory power improves a lot, while the beta of ΔVWD and ΔCCI appear more significant than in two-index model slightly.[24] Specifically, 150 out of 383 sentiment coefficients associated with ΔVWD and 182 with ΔCCI are statistically significant; it indicates us that the sentiment is much easier to be captured in six-index model. Interestingly, the sensitivity of individual stock returns to market factor is substantially weaker than all of previous regressions. The betas of the size factor are more significant than other factors; they are much easier to affect the returns on individual assets. These results corroborate our previous work; the betas for the investor sentiment and for the size are significant than the betas associated with the B/M and momentum, investor sentiment is a systematic factor in the individual stock return generating process.

Table 2.6 clearly shows the times of sensitivities of mutual fund and individual stock returns on various factors are significant at 5% level in both two-index model and six-index model. As we discussed above, having the high individual ownership structure, individual stocks should be the most easily influenced portfolios by sentiment. These results associated with our previous findings to support the argument that investors require high returns to compensate their investor sentiment. Overall, all of the evidences in our diversified portfolios show that sentiment is an important factor in affecting the returns. Our UK empirical result is consistent with LST's (1991) investor sentiment hypothesis. Interestingly, we find that the size factor can be related to the return generating process more frequently than investor sentiment.

[24] Inconsistent with us, Dokas and Milonas (2004) in their study on Greek stock market, using sample in Athens Stock Exchange, find that in the case of the six-index model, the beta associated with sentiment is less significant than the one in two-index model. The regression results see Doukas, John A., and Nikolaos T. Milonas, 2004, "Investor Sentiment and the Closed-end Fund Puzzle: Out-of-sample Evidence"

Table 2.6

Times of factors are significant at 5% level: regression based on individual stocks

Panel A

Models	$R_{it} = \alpha_i + \beta_{im} R_{mt} + \beta_{i0} \Delta VWD_t + \varepsilon_{it}$	$R_{it} = \alpha_i + b_i R_{mt} + s_i SMB_t + h_i HML_t + w_i WHL_t + \beta_i \Delta VWD_t + \varepsilon_{it}$
Numbers	383	383
Rmt	28	18
ΔVWD	127	150
SMB	-	247
HML	-	73
WML	-	26

Panel B

Models	$R_{it} = \alpha_i + \beta_{im} R_{mt} + \beta_{i0} \Delta CCI + \varepsilon_{it}$	$R_{it} = \alpha_i + \beta_i R_{mt} + s_i SMB_t + h_i HML + w_i WHL_t + \beta_i \Delta CCI + \varepsilon_{it}$
Numbers	383	383
Rmt	36	34
ΔCCI	145	182
SMB	-	252
HML	-	84
WML	-	31

Notes: This table reports the time series relationship between monthly excess returns on all individual stocks, sentiment proxy (ΔVWD and ΔCCI respectively), and the monthly excess return on the FTSE All Shares, which is used as a proxy for the market return (Rmt). SMB is the portfolio of small stocks minus big in terms of size, HML is high minus low in terms of Book to Market, and WML is winner minus loser in terms of momentum.

2.5 Summary and Conclusions

In this paper, we tested the LST's (1991) theory that small investor sentiment has a significant impact on stock risk premium and changing sentiment of individual investors explains the discounts of closed-end funds. In the investor sentiment theory, discounts are low when individual investors are optimistic on their future returns and high when investors are pessimistic. Discounts are existed in long run not only due to the inherent risk in the portfolio but also the unpredictable sentiment risk in holding a closed-end fund. However, this theory appears to be inconsistent with much empirical evidence of the performance of the closed-end fund, and several indications of this theory have been involved in controversy.

Along these lines, Elton et al (1998) are the first to raise the methodology that use out of sample test to investigate the closed-end fund discount puzzle and investor sentiment, moreover, Dokas and Milonas (2004) develop the method by using Greek evidence. Because without testing the findings outside the stock market in where they were discovered, it is still not robust enough to prove whether the results are merely limited in the US market. Accordingly, we use UK evidence to examine the significance of investor sentiment in return generating process out of US market. In order to test whether the discounts of closed-end funds are indeed related to the investor sentiment which is measured by the change in the discounts of closed-end funds, especially, we collect the newest dataset, add Carhart (1997) momentum factor to Fama-French three factor model to pay attention to the UK capital market which has quite close characteristics while comparing to US market,

The UK stock market is a natural candidate to be examined since the composition of individual investors in UK is almost as same as in US. Furthermore, the UK stock market has experienced both a dramatic price run down and an unexpected bullish trend during the 1990-2008 periods, so the investors encountered both pessimistic and optimistic psychology, the investor sentiment should be more notable. Besides, all the closed-end funds in our sample are trading at, on the average, 15% discount during 1990-2008 periods. Using the invulnerable sample and data, it is no doubt that our study provides a distinct opportunity to investigate whether the investor sentiment plays a key role in asset pricing.

The basic finding of this paper is that our evidence is consistent with the view of LST (1991) that investor sentiment influences the risk of common stock. According to our results, we are against to the argument of Elton et al (1998), Dokas and Milonas (2004) who indicate that investor sentiment cannot be related to the return generating process. We detect the investor sentiment in explaining closed-end fund discounts in a capital market whose characteristics are expected to be more identical to the capital market where the investor sentiment is originated in. This provides more powerful support to the claim that investor sentiment represents systematic asset pricing risk. In the regression results of our two-factor and five-factor model, we also find that while entering the return generating process, the sentiment factor is significant as well as size which is not deemed as systematic asset pricing factors so that they can be a benchmark of comparison. Our models also detected that investor sentiment is more prevalent in smallest size portfolio than other portfolios; it offers us additional evidence to support another aspect of LST's (1991) theory which is known as small firm effect. When we investigate the patterns of return sensitivity to the sentiment factor onto sector indices and individual stocks, there is a strong evidence to consistent with LST (1991) that they are more sensitive to the sentiment factor due to higher individual ownership.

Overall, we documented that there is an evidence to support the investor sentiment as an important factor to represent systematic risk in return generating process and the discounts of closed-end funds can be explained by investor sentiment theory. Dimson and Minio-Kozerski (1999) propose that the price performance of closed-end funds is basically rational and the market appears to be efficient when dealing with open-ending by event study. Several kinds of event studies such as IPO patterns (cherkes, 2003) and managerial performance (Chay and Trzcinka, 1999; Berks and Stanton, 2007) have been linked to the closed-end fund discount puzzle and investor sentiment. Thus, the event studies on the other aspects which are usually ignored by researchers, such as board structure of the corporate, mergers and acquisitions and corporate diversification, remain a topic for future research.

CHAPTER 3

INVESTOR SENTIMENT AND ETF PRICE PREMIUM

3.1 Introduction

Exchange traded funds (ETFs) have become an increasingly important and popular security in the index mutual fund product category. These investment hybrids of open-ended funds and common stocks hold a fixed basket of stocks based on an underlying index, with identical stocks and weights, but they trade throughout the day at market-determined prices on a stock exchange. They can be purchased on margin and sold short; about 90% of existing exchange traded funds are designed to track the market indices. The inception of the Standard & Poor Depositary Receipts (SPDRs) on the AMEX Exchange in 1993, and the proliferation of iShares, DIAMONDS, and Qube (Q) products have led to a rapid development in ETFs in terms of both number of funds offered, and total assets. This growth and popularity have enhanced investment choices and brought new challenges to investigate the role played by ETFs in professional portfolio management, and to identify the factors that drive investors to invest in these products.

Recent literature has studied numerous issues related to the impact of ETFs on our financial markets. Several authors analyse the advantages ETFs offer to investors in developed markets such as the US and Australia (see Gastineau, 2001, and Gallagher and Segara, 2005, respectively). Other studies focus on the impact of ETFs on the index futures market, changes in the market liquidity, and pricing errors of the underlying stocks these ETFs hold (see Switzer, Varson and Zghidi, 2000, Hedge and McDermott, 2004, and Ackert and Tian, 2000, respectively.). Meanwhile, Ackert and Tian (2000), Elton et al. (2002), and Poterba and Shoven (2002) investigate ETF pricing and performance, including, but not limited to, how ETF pricing differs from net asset value (NAV).

However, little work has been done to extend our knowledge of what actually drives investors to invest in the ETFs, and to identify the significant factors in that investment decision. Therefore, we are interested to investigate what motivates ETF investors to trade at market prices which, in general, deviate from the fundamental NAV per share. These deviations may be statistically significant given that, unlike closed end funds whose prices also deviate from the NAV, ETFs, through a mechanism known as redemption in-kind, allow institutional investors, also called Authorized Participants,[25] to potentially earn a profit by arbitraging away these pricing deviations by creating and deleting outstanding shares of the ETF. Hence, we are motivated to identify the factors that may impact on the determination of these premiums and discounts to the NAV. Specifically, we intend to examine whether these pricing deviations are caused by investor biases, or by factors unrelated to risk as investor sentiment proxies. We will also examine whether market capitalization affects the pricing of the sample of ETFs used in this study.

[25] Authorized Participants are those institutional investors authorized to initiate creations and deletions.

This paper seeks to increase our understanding of ETFs by analysing the effects of investor sentiment not related to risk, to determine 1) whether investor sentiment orthogonal to common risk factors plays a role in the pricing deviations from the NAV of ETFs, and 2) whether the significance of sentiment varies across various ETF characteristics. It attempts to shed light on whether and what factors unrelated to risk drive the trading of ETF investors, subsequently resulting in price deviation. To the best of my knowledge, this study is the first to explore our understanding of ETF price deviation and the question of whether individual investors affect these activities significantly in the UK market.

Hughen (2001) suggests that many short-term investors like to trade in ETFs since they offer potentially higher profits; moreover, the ability to short ETF shares and trade them on margin may also be attractive. Poterba and Shoven (2002) compare the pre-tax and after-tax returns of SPDRs and Vanguard Index funds, tracking the S&P 500 Index, and show that individual investors may prefer ETFs to other similar investment products due to their preferential tax treatment. Moreover, institutional investors may be attracted to ETFs because of the growth in index investing in the US, another reason is that the price deviations from the NAV offer an opportunity for arbitrage by creating and deleting shares (see Bhattacharya and Galpin, 2005). This creation and deletion mechanism also offers institutional investors an efficient means of transacting in small and medium capitalized securities. Following previous research, my interest is in whether these different types of investors are motivated by factors which are considered not to be related to risk or, in accordance with the efficient market hypothesis, strictly driven by knowledge about changes in fundamental risk.

Lee, Shleifer and Thaler (1991) find that small investor sentiment has more significant effect on the pricing of small capitalized stocks than on that of large capitalized stocks. Additionally, they find that institutional fund managers tend to trade according to the need for liquidity. The present study examines whether or not these findings hold for ETFs, and uses direct measures of individual investor sentiment to investigate to what extent the investor bias may affect ETF pricing. We also attempt to check whether the investor biases affect the price deviations of ETFs, or whether other factors, such as liquidity, are motivators.[26]

Since the ETFs are traded on the open market, and due to the intraday trading, the trading price for an ETF may be affected by non-risk related factors. The traders' perceptions and expectations of the market may also affect the demand and thus drive market prices. Measures of investor sentiment, considered as a proxy for the extent to which investors have expectations about the market, i.e. the market will be better/bullish or worse/bearish, provide us with an important approach to test the impact of these non-risk related factors. Additionally, the dataset used in this study makes it possible to analyse investor sentiment on each individual ETF separately; this is critical to disentangle the effects these specific sentiment sets have on ETF price deviation.

Further investigation of the ETF and investor sentiment measures provides an opportunity to analyse the differences between individual ETFs, which could have some implications for the traditional risk-based asset pricing model literature. Specifically, after accounting for the

[26] See Chordia, Roll and Subrahmanyam (2001) and Datar (2001) for a discussion on the role of liquidity in trading activity and closed end funds, respectively.

portion of sentiment not attributable to risk,[27] we test whether investor sentiment has a significant impact on driving individual ETF performance and its market price. We are also interested to examine whether this relationship differs across ETFs based on size. This paper contributes to the existing literature by adding investor sentiment to the traditional factors which affect ETF characteristics such as pricing, and by considering the interplay between ETFs and investor behaviour in the market.

3.2 Literature Review

3.2.1 Investor Sentiment and Noise Trader Literature

Tracking the indices has become the preferred investment approach of fund managers. Bhattacharya and Galpin (2005) show that in the US, fund managers' stock picking and active management declined gradually from a high of almost 60% in the 1960s to a historical low of 24% in the 2000s. Results show that when taking expenses into account, active managers do not consistently outperform the market returns. Consequently, we are interested to examine whether, given the unique ETF trading mechanism, non-risk related investor perception plays an important role in explaining demand and price in the index markets with ETF products.

[27] It is of interest to determine whether there is a significant difference in the level of institutional versus individual investor sentiment not attributable to risk.

Most papers use measures of investor sentiment to estimate investor optimism or irrational investor pessimism of the market. The studies test whether sentiment is related to some fundamental aspect of a security, such as returns, volatility or price. If uninformed noise traders or irrational investors base their trading decisions on sentiment rather than fundamentals, then measures of that sentiment may have explanatory power for asset pricing.

Black's (1986) theory of "noise traders" suggests that these investors cause the market to be inefficient, but often prevent us from taking advantage of inefficiencies. Noise is the opposite of information but essential to market liquidity. A large number of papers test the effect of investor sentiment measures on financial markets; however, most focus on the closed-end mutual fund or common stocks and their returns. Shleifer and Summers (1990), and DeLong, Shleifer, Summers and Waldman (1990) provide evidence that the less than fully rational investors could be able to affect the price, and these noise traders play a key role in our financial markets, which poses a huge challenge to the traditional efficient market hypothesis. Gemmill and Thomas (2002) use a general sample of closed-end funds in the UK market to investigate the reason for closed-end fund discount. Using retail investor flows as sentiment proxy they find that the fluctuations in discounts are generated from the function of irrational trader demand. However, they argue that the noise trader theory has little explanatory power for the long-run persistence of closed-end fund discounts.

Lee, Shleifer and Thaler (1991) (henceforth LST) examine the "closed-end fund puzzle" and conclude that there is a relationship between the closed-end fund discount and investor sentiment. Their result suggests that changes in the individual investor sentiment can explain the fluctuation of the discount, and subsequent changes in investor sentiment make closed-end funds riskier than the underlying assets they hold. Additionally, they find that the smaller stocks tend to be more VULNERABLE to the change of retail investor sentiment. This is of interest because we will examine the effects of investor sentiment across different sizes of ETFs and, if we find consistent evidence of LST's (1991) conjecture regarding size, the price deviations of ETFs tracking benchmarks holding smaller stocks should be greater than the deviations for ETFs that track indices holding large-capitalization stocks.[28]

However, Chen, Kan and Miller (1993) challenge the findings of LST (1991). Using another dataset, they suggest that LST's (1991) results are highly restricted to a fixed time period, and not sufficiently robust to an alternative sampling period. Moreover, while according to LST's (1991) theory, investor sentiment, proxied by the changes in closed-end fund discount, plays a significant role in explaining the return generating process for common stocks, Elton et al. (1998) propose that the closed-end fund discounts can be explained by factors unrelated to sentiment.

Neal and Wheatley (1998) examine three indirect measures of investor sentiment, namely closed-end fund discount, mutual fund redemptions and odd-lot ratios, in explaining the stock return generating process. They find that the closed-end fund discount and mutual fund redemptions have predictive power in determining the premium in returns for both small and large firms, but there is no evidence that the odd-lot ratios can predict the returns.

[28] Delong, Shleifer, Summer and Waldmann (1990) and Lee, Shleifer and Thaler (1991) note that if noise traders, as proxied by investor sentiment, affect the mutual fund as well as the assets held by the fund, then there should be changes in NAV as well as in the price of the underlying stock. Given that these move in the same direction there should not be significant changes in the discounts of closed-end funds in this situation.

Bodurtha et al. (1995) investigate whether the measures of US investor sentiment affect the premiums and discounts of closed-end country funds, which invest solely in a specific foreign market[29] and also sell at premiums or discounts to their NAV. Consistent with investor sentiment hypothesis, when the investors are optimistic/pessimistic about a security, the price will deviate from the NAV and subsequently there will be a mean-reversion.

Brown (1999) finds that investor sentiment is significantly related to the price volatility of closed-end funds. Wang et al. (2006) document that while previous studies examine whether sentiment has predictive power on volatility, they always ignore the fact that the lagged returns information could also be useful for this purpose. Brown and Cliff (2004) use the direct measures of sentiment, to test whether they can predict short-run market returns. They find that changes in future investor sentiment are caused by market returns, but not vice versa. They also suggest that there is a significant relationship between contemporaneous returns and changes in sentiment. Furthermore, they provide evidence that the contemporaneous returns of large stocks are highly related to the institutional investor sentiment. In a later work, Brown and Cliff (2005) show that the market returns over the next 1-3 years can be predicted by a direct survey measure of investor sentiment. They also suggest that this measure has the ability to explain deviations from intrinsic value as measured by other stock price models documented in the literature.

Lemmon and Portniagina (2006) find that investor sentiment proxied by the Index of Consumer Sentiment (ICS) provided by the University of Michigan has the ability to predict

[29] A foreign market is labelled as such if the shares in the country fund are foreign to the exchange it sells on.

the returns of smaller capitalized stocks. Baker and Wurglur (2006) study how investor sentiment affects the cross-section of stock returns. The evidence shows that those securities whose valuations are highly subjective and difficult to arbitrage are more sensitive to the fluctuation of investor sentiment. For example, when the sentiment is relatively low, the returns are high for small stocks, young stocks, high volatility stocks, unprofitable stocks, non-dividend-paying stocks, extreme growth stocks, and distressed stocks. Similarly, in a more recent study, Baker et al. (2010) construct investor sentiment indices for six major stock markets. They combine them into one global index and then decompose that index into six local indices. They find that both global and local sentiment have contrarian predictive power when explaining country-level returns. When the global or local sentiment is high, the categories of difficult to arbitrage and value stocks have a low future return. The authors also investigate how global sentiment emerges and propagates; they find some evidence that private capital flows are one mechanism by which sentiment spreads across markets, helping to form global sentiment.

3.2.2 ETF Literature

While academic literature has long shown substantial interest in the performance and behaviour of traditional mutual funds, since 1993, with the launch of the first ETF, this relatively new investment instrument has become the focus of increasing research attention. Elton, Gruber, Comer and Li (2000) study the pros and cons of the Standard and Poor's Depository Receipts (SPDRs) and conclude that ETFs hold the advantages of both open and closed-end funds. ETFs trade throughout the trading day and at a price close to the NAV, whereas closed-end funds trade at high premiums/discounts to their NAV. In an enlightening paper about ETFs in the US market, Gastineau (2001) describes the main types of ETF, the exchanges where they are traded, their characteristics and the operating mechanism. He also identifies the benefits of ETFs in terms of flexibility, convenience, tax efficiency, risk diversification and cost advantages.

Ackert and Tian (2000) study the pricing of the Standard and Poor's Depository Receipts. They find that the trading price of SPDRs does not significantly deviate from the NAV. The main reason for the slight price deviation is the opportunity for low cost arbitrage, whereby large investors exhibit efficient performance by using arbitrage strategies which eliminate the gap between the trading price and the NAV. It is interesting that with higher arbitrage costs, the mid cap SPDRs trade at a relatively large discount. Although the price deviation for US ETFs is small, the international ETFs exhibit more significant mispricing. Jares and Lavin (2004) use Japan and Hong Kong iShares data to provide evidence that deviations exist between the ETF price and the NAV, and that these deviations are positively related to the potential profit opportunity of subsequent ETF returns. Compared to a buy-and-hold strategy, this observation provides more return turnovers. Engle and Sarkar (2006) focus on whether the errors of reported prices and NAVs can explain the short-term mispricing. They suggest that the ETF mispricing in the US is very small and may last only a few minutes; however, for the country funds, the price deviation performs persistently.

Boehmer and Boehmer (2003) find that the entry of a new product, the ETF, to the NYSE in 2001 led to a dramatic improvement in liquidity. Their findings strongly support the view that the competition for order flow among market centres improves the market liquidity, and is not likely to affect price discovery adversely. Hedge and McDermott (2004) examine the market liquidity effects of the underlying stocks of the Dow Jones Industrial Average and the NASDAQ after the introduction of DIAMONDS and Qubes.[30] Based on the intraday data over the first 50 trading days, they find that DIAMONDS and Qubes, or "basket trading", are associated with significantly lower liquidity costs than the corresponding portfolios holding the same component stock. Additionally, they indicate that the higher market liquidity of the baskets is decided mainly by lower adverse selection cost of trading in the composite securities. Their findings show that the market in DIA and Q's are relatively more liquid, and that basket trading improves the market liquidity of corresponding component stocks.

Poterba and Shoven (2002) compare the returns of SPDRs and Vanguard Index funds, which both track the S&P 500 Index, and find that these funds perform similarly. They also point out that ETFs take advantage of tax efficiency due to the "in kind" redemption process, which reduces the distribution of taxable realized capital gains.

Numerous papers focus on the relationship between the ETFs and index futures market. Park and Switzer (1995) examine how the TIPs (Toronto 35 Index Participation Units[31]) impact on the Canadian index futures market. The results show that TIPs benefit the index futures market in both total trading volume and overall pricing efficiency. Similarly, in research focused on the US market, Switzer, Varson, and Zghidi (2000) and Chu and Hsieh (2002)

[30] DIAMONDS are units of the exchange traded fund that mimics the Dow Jones Industrial Average by holding the same 30 component stocks as that Index. Qubes are units of the exchange traded fund that holds the same component funds as the NASDAQ 100.

[31] In March 1990 the Toronto Stock Exchange developed TIPs, which represent an interest in a trust that holds baskets of the stocks that make up the Toronto 35 Index. TIPs are akin to ETFs in the US market.

find that the introduction of SPDRs improved the pricing efficiency of the S&P futures market because it mitigated the pricing errors in the S&P Index futures contracts and simplified the short arbitrage process.

Gallagher and Segara (2005) focus on the trading and return characteristics of Australian ETFs. They demonstrate that classical ETFs compensate investors with returns before expenses in proportion to the benchmark performance. Furthermore, ETFs exhibit lower tracking error relative to the corresponding index funds. They also find that the ETFs' trading price deviations from NAV are infrequent and not sizeable. More interestingly, Charupat and Miu (2010) find differences in the behaviour of price deviations of bull and bear ETFs. On average, bull ETFs trade at a discount or a slight premium to NAV, while bear ETFs trade at a larger premium. This is consistent with their other finding that premiums occur more frequently than discounts for all bear ETFs, while discounts are observed more frequently than premiums for all bull ETFs. In comparison, they do not find any consistent pattern for traditional ETFs. Milonas and Rompotis (2006) use Swiss evidence to study the performance and trading characteristics of a sample of 36 ETFs during the period 2001-2006. They find that Swiss ETFs fail to outperform their underlying indices and expose investors to greater risk. The tracking error observed is substantially high, with an average of approximately 1.02%. This tracking error is positively related to the management fees and expenses, and negatively related to the ETF returns

Moreover, Ascioglu et al. (2008) and Chelley-Steeley and Park (2010) show that the information asymmetry present in ETFs is lower than for individual securities, giving rise to lower adverse selection costs. This suggests that if information asymmetry is an important influence over intraday trading patterns, then ETFs should display more homogenous trading volumes than observed in stock markets. Because information asymmetries are lower for ETFs, informed traders have less information advantage than they do in markets for individual securities, and this reduces the tendency for concentrated trading bouts to occur early on in the trading process.

Innovation in financial markets is essential to their well-being and development. Fuhr (2001) considers ETFs as the leading financial innovation in the past decade. Although the literature discussed here is not exhaustive, it may still provide us with relatively rich information to gain a better understanding of ETFs. Our study aims to extend the understanding of ETF performance, its mechanism and its relations with the market and various market factors.

This study will help to shed light on the role played by investor sentiment in determining the price deviation in ETFs. Specifically, we provide evidence of the extent to which investor sentiment orthogonal to risk significantly affects pricing deviations of ETFs. Further, inspired by the market capitalizations findings of Lee, Shleifer and Thaler (1991) and Brown and Cliff (2004), we examine whether the significance of the sentiment measures differs across ETFs holding stocks with varying firm characteristics.

3.2.3 The Formal Hypotheses

Brown (1999) notes that “it would be interesting to replicate our cross-sectional tests with US data and thereby verify, in a different environment, that it is the interplay of noise, arbitrage and expenses which cause closed-end funds to trade at market prices that deviate from fundamental values”. In line with this, we believe the UK market offers an attractive context in which to study ETFs, since it is well regulated and developed. This paper tests the following null hypotheses:

1) H0: Investor sentiment has a significant effect on the pricing of UK exchange traded funds.

2) H0: Investor sentiment has an equal impact on the pricing of exchange traded funds holding stocks of varying characteristics in the UK market.

Our expectation is to reject the null of no significance. Generally, we expect that individual investor sentiment will have a significant and strong impact on our sample because we consider that those investors who have irrationally biased perceptions, i.e. noise traders, who may be considered as less sophisticated, may drive the trading price away from the ETF fundamental value. We also expect the respective measures of investor sentiment effect on the price deviation to vary across our sample group according to different market capitalizations. Specifically, the impact of sentiment should be greatest on small cap ETFs.

3.3 Data

3.3.1 ETF Descriptive Statistics

In this paper, our sample is constructed from UK iShares listed in the London stock exchange. Our sample is based on the daily data from 01/01/2007 to 31/08/2010 for 44 ETFs. The reason for this choice is that the iShares dominate the global ETFs, with over $620bn[32] invested in 474 funds. 43.0% of the world's total ETF assets under management are invested in iShares funds. Hence we believe that the UK iShares provide us with a good opportunity to study the UK ETF market. The sample consists of 44 ETFs listed in the London Stock Exchange. Although there are actually more ETFs listed in the Exchange, many of them either have missing data through the resource provider we use, or have only recently been listed. The data related to the ETFs in this paper were collected from Datastream and the iShares website. All other data were obtained from the Xfi Centre for Finance and Investment. As Michou, Mouselli and Stark (2007) note, there is no freely downloadable equivalent to the data on Ken French's US website; however, Gregory, Tharyan and Huang (2009) remedy this situation by making available the Fama-French and Momentum portfolios and factors for the UK market to the wide community of UK academic and post-graduate researchers.

In order to develop the descriptive statistics, it is important first to show the calculation methods of ETF price deviations. There are two main notations in the previous literature, of

[32] Source: BlackRock, data as at end H1 2011

which one is computed as the difference between the ETF price and the fund's NAV, divided by the NAV (Ackert and Tian, 2008):

$$premium_t = \frac{p_t - NAV_t}{NAV_t} \tag{3.1}$$

The other uses the natural log of the fractional difference between the price and NAV (Engle and Sarkar, 2006):

$$premium_t = \log p_t - \log NAV_t \tag{3.2}$$

From both equations, we may obtain the premium of the ETF; a discount is a negative value of premium. In each column of the ETF properties, the first row refers to the first equation and the second row to the second equation.

Following the first method, for 31 of 44 funds the average deviation in price from NAV is positive (a premium), whereas for 11 funds a discount is observed; there are also 2 funds with no discount or premium, on average. With the second method 12 funds have neither discount nor premium, 8 funds exhibit negative average price deviation, and 24 funds have premiums, on average. When we focus on individual funds, by both methods, the percentage of premiums is greater than the discounts and nets; the numbers of premiums, discounts and nets are close by two different methods.

The largest premium on any day in our sample is 25.79% for ETF44, while the largest discount observed is 18.96% for ETF30, based on the first method. With the second method, the same ETFs exhibit the largest premium and discount, but the absolute values are much smaller, at 9.97% for premium and 9.13% for discount. We observe that no matter which method we use to calculate the price deviation, the average deviation is more often a premium than a discount, which may result from the redemption and creation process. An ETF that trades at a discount can be redeemed by a qualified investor with relatively low cost, whereas creating new units is more costly for the trust and may be implemented with a greater time lag. Therefore, it is not surprising that we see fewer discounts.

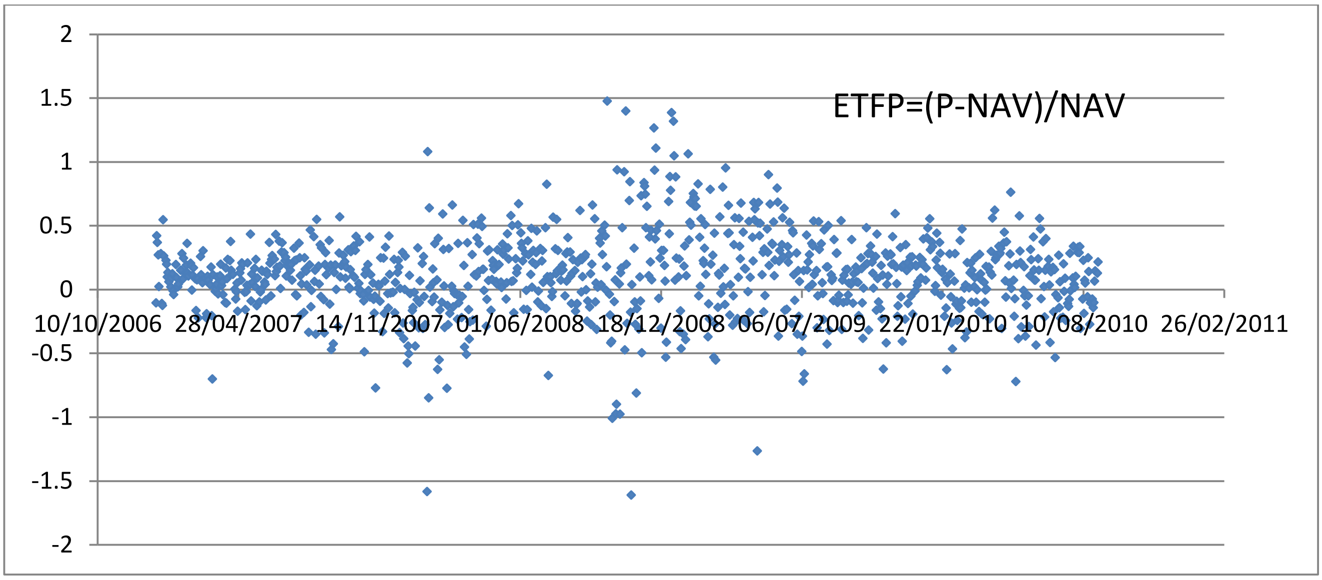
Figure 3.1 also investigates the distribution of the ETF price deviation. Using the first method, most of the funds deviate significantly from their fundamental values by more than 0.5%, while with the second method the situation is dramatically different, and very few fund price deviations are observed. Furthermore, all of the standard deviations for the second method are much smaller than those for the first method.

Comparing our descriptive statistic figures to previous studies, using equation (3.1), Ackert and Tian (2008) find that in the US, over a sample period from June 3, 2002 to January 13 2005, 19 out of 28 funds have a premium, while 9 discounts are observed; in our study 31 of 44 funds have a premium, 11 funds have a discount and there are 2 net funds. Hence, the percentage of premium in both samples is very close; however, the average premium in Ackert and Tian's (2008) study is very small, at 0.0154%, compared to our 0.117%. With regard to the largest premium and discount, their findings are 9.46% and 8.5%, whereas ours are 25.79% and 18.96%. From these figures, we find that using equation (3.1), UK ETFs exhibit larger price deviation, and are more volatile, than US ETFs. Following approach (3.2), Engle and Sarkar (2006) find that out of a sample of 21 US ETFs, 15 have positive price deviation while 6 have negative deviation. The average premium is 0.0109%, which is even smaller than the results of Ackert and Tian (2008), whereas we obtain 0.047%. The average standard deviation is 0.1833%, with funds performing with great stability during the sample period.

Overall, we may conclude that UK ETFs show larger values of all statistics under both equations. The premiums in the UK deviate more from zero and the distribution appears to be more volatile than in the US.

Figure 3.1 plots the price deviations for the UK ETFs. Overall, the fund price closely tracks fundamental value and the premium does not vary far from zero over time. The behaviour of the price deviation is stable over the early sample period; the market prices of ETFs are close to their fundamentals. In the middle of our sample period, the premiums are quite erratic, with what appear to be large and persistent deviations from zero. In addition, the distribution appears to have become more concentrated around zero in recent years. As with the developed markets ETFs, the distribution seems to converge toward fundamental price over time. Looking at individual funds, we find that the trend of the price deviations under the two methods over our sample period is exactly the same; however, the natural log measure of price deviation is less volatile than the division measure.

Panel A



Panel B

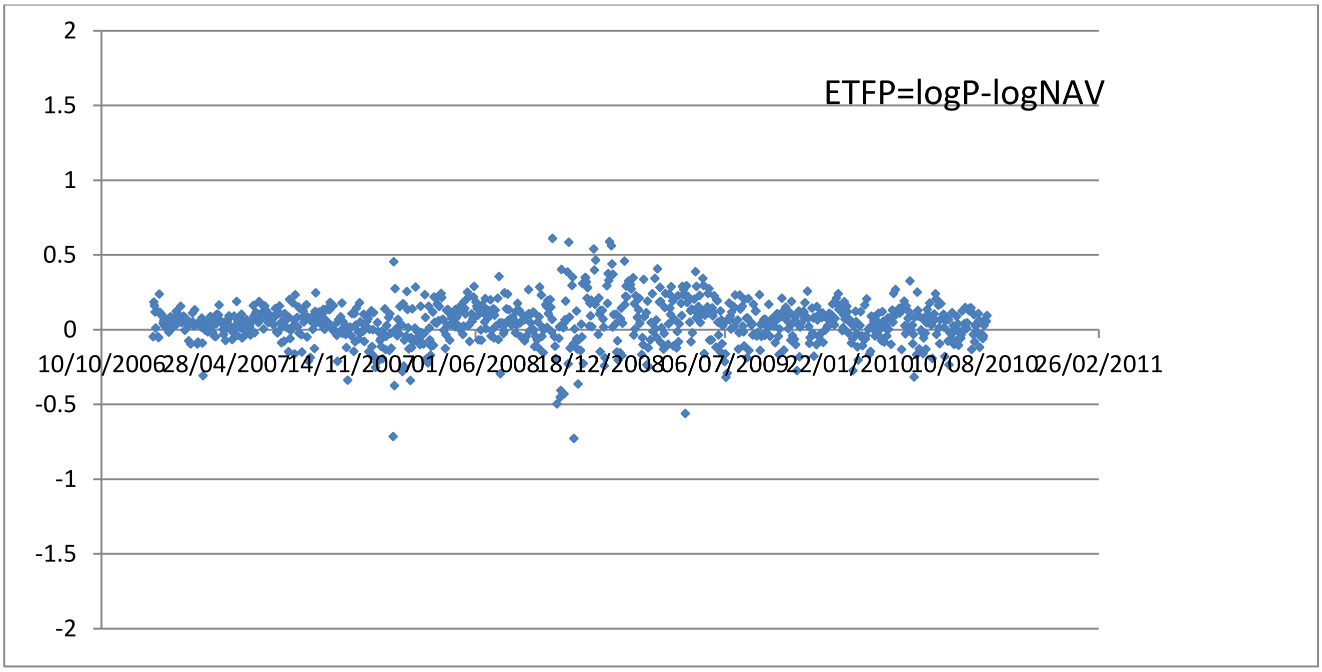


Figure 3.1 Price deviations for two equations

Table 3.1 presents all 44 ETFs in the sample grouped by capitalization. This table indicates a positive and significant relationship between fund size and average value of price deviation. The medium capitalization funds have the smallest standard deviation; both the occurrence of price deviation and the number of absolute values larger than or equal to 0.5% are less than for large cap and small cap funds. Therefore, it seems that the price deviation is not very relevant to their size. The trend is very similar for both equations. Based on our findings above, we use equation (1) for the following work, because it gives larger figures and more volatile data, which can make our regression more precise and convenient.

Table 3.1 also presents the first-order to fifth-order autocorrelation coefficients, to explain the details of premium correlation over our sample period. From Panel B, we can see that the first-order correlations of 39 of the 44 ETFs are positive, which indicates that momentum may exist in fund premiums. Furthermore, nearly all of the t-values of the first-order autocorrelation coefficients are significant at 5% level; the numbers of significance from first-order to fifth-order are: 35, 25, 14, 18 and 7. We find that the serial dependence becomes weaker beyond the first lag; however, the dependence is still significant after five lags (7 of 44 funds).

Table 3.1 Funds Information

Panel A: Descriptive statistics

	Obs. (%)	Mean (%)	Med. (%)	Max (%)	Min (%)	St.Dev. (%)	Dis (No.)	Net (No.)	Prem (No.)	ABS≥0.5% (No.)	Avg.Mkt. Value (Millions)
Large Cap.	14355	0.22	0.15	25.79	-18.96	1.70	5622	124	8609	6915	1025.86
		0.09	0.06	9.97	-9.13	0.73	5447	268	8643	3455	
Mid Cap.	14355	0.08	0.05	13.05	-11.72	0.56	5668	267	8420	2613	210.26
		0.03	0.02	5.33	-5.41	0.24	5487	631	8237	424	
Small Cap.	13398	0.05	0.05	15.96	-14.55	1.11	5864	150	7384	4657	79.68
		0.02	0.02	6.43	-6.83	0.48	5882	345	7171	2063	

Notes: Panel A reports the descriptive statistics of different size which is grouped by all the 44 ETFs capitalization.

Panel B: ETFs Autocorrelation

	Obs.	1st-Order	2nd-Order	3rd-Order	4th-Order	5th-Order	Avg. Mkt Value (Million)
ETF1	952	0.1668	0.1096	0.1059	0.1077	0.0931	2387.29
		(5.15)*	(3.36)*	(3.24)*	(3.30)*	(2.88)*	
ETF2	952	0.3816	0.2002	0.8652	0.0533	0.0693	265.47
		(11.80)*	(5.80)*	(2.59)*	(1.62)	(2.23)*	
ETF3	952	0.1145	0.0250	0.0573	0.0133	0.0349	63.59
		(3.52)*	(0.74)	(1.75)	(0.41)	(1.07)	
ETF4	952	0.1907	0.0818	0.0836	0.0620	0.0247	82.32
		(5.87)*	(2.48)*	(2.53)*	(1.88)	(0.76)	
ETF5	952	0.5768	0.2032	0.0097	0.0631	0.0653	598.60
		(17.8)*	(5.43)*	(0.26)	(1.69)	(2.01)*	
ETF6	952	0.0210	0.2191	-0.1424	-0.0309	-0.0388	125.01

		(0.65)	(6.74)*	(-4.32)*	(-0.95)	(-1.19)	
ETF7	952	0.0592	0.1094	0.0577	0.0679	-0.0187	214.05
		(-1.82)	(3.37)*	(1.77)	(2.09)*	(-0.57)	
ETF8	952	0.0383	0.0504	0.0573	0.1185	-0.0063	139.51
		(1.18)	(1.56)	(1.77)	(3.67)*	(-0.194)	
ETF9	952	0.0513	0.0535	-0.0120	-0.0461	-0.0430	94.60
		(1.58)	(1.65)	(-0.371)	(-1.42)	(-1.32)	
ETF10	952	0.3761	0.1754	-0.0010	0.0550	0.0386	263.27
		(11.6)*	(5.06)*	(-0.03)	(1.58)	(1.19)	
ETF11	952	0.0142	-0.0116	0.0334	0.0500	0.0616	265.46
		(0.44)	(-0.36)	(1.03)	(1.53)	(1.90)	
ETF12	952	0.2309	-0.0862	0.0266	-0.0016	0.0878	76.42
		(7.13)*	(-2.59)*	(0.80)	(-0.05)	(2.71)*	
ETF13	952	0.1426	-0.0222	-0.0311	0.0018	0.0185	184.87
		(4.39)*	(-0.68)	(-0.95)	(0.06)	(0.57)	
ETF14	952	0.2199	0.0334	-0.0360	0.0976	0.0291	187.62
		(6.77)*	(1.01)	(-1.09)	(2.94)*	(0.90)	
ETF15	952	0.1631	0.0396	0.0474	0.0432	0.0467	292.48
		(5.02)*	(1.12)	(1.44)	(1.31)	(1.44)	
ETF16	952	0.1222	0.1051	-0.0070	0.0671	0.0314	66.05
		(3.76)*	(3.22)*	(-0.21)	(2.05)*	(0.97)	
ETF17	952	0.1915	0.3725	0.1096	-0.1068	0.0100	3014.29
		(5.89)*	(11.30)*	(3.14)*	(-3.24)*	(0.29)	
ETF18	952	0.1856	0.0533	-0.0640	0.0605	-0.0165	117.21
		(5.71)*	(1.62)	(-1.94)	(1.83)	(-0.51)	
ETF19	952	0.9000	0.0202	0.0029	0.0756	-0.0043	364.85
		(2.77)*	(0.62)	(0.09)	(2.32)*	(-0.13)	

ETF20	952	0.2205	0.0675	-0.0205	0.0656	-0.0197	182.64
		(6.78)*	(2.03)*	(-0.62)	(1.97)*	(-0.61)	
ETF21	952	0.1481	0.1184	-0.0532	0.1587	0.0518	63.90
		(4.56)*	(3.65)*	(-1.63)	(4.89)*	(1.59)	
ETF22	952	0.1199	0.0716	-0.0294	0.0457	-0.2927	40.21
		(3.69)*	(2.19)*	(-0.90)	(1.40)	(-0.90)	
ETF23	952	0.1608	0.1120	0.0585	0.1164	0.0070	69.97
		(4.95)*	(3.42)*	(1.78)	(3.56)*	(0.22)	
ETF24	952	-0.1127	0.0140	0.0256	0.0400	0.0109	106.35
		(-3.47)*	(0.43)	(0.78)	(1.21)	(0.34)	
ETF25	952	-0.1880	-0.0823	-0.0326	-0.0538	-0.0520	52.28
		(-5.79)*	(-2.49)*	(-0.99)	(-1.63)	(-1.60)	
ETF26	952	0.4914	0.0763	-0.0882	0.0183	0.1092	226.55
		(15.2)*	(2.12)*	(-2.45)*	(0.51)	(3.38)*	
ETF27	952	0.1888	0.1211	0.1225	0.0673	0.0860	237.66
		(5.83)*	(3.68)*	(3.73)*	(2.05)*	(2.66)*	
ETF28	952	0.2942	0.1082	-0.0672	0.0401	-0.0078	230.61
		(9.05)*	(3.20)*	(-1.98)*	(1.18)	(-0.24)	
ETF29	952	0.0612	0.1729	0.1767	0.0354	0.0276	199.91
		(1.88)	(5.31)*	(5.44)*	(1.09)	(0.85)	
ETF30	952	0.0098	0.0362	-0.9963	-0.0251	-0.0158	491.06
		(0.30)	(1.11)	(-3.08)*	(-0.77)	(-0.49)	
ETF31	952	0.1747	0.0983	0.0477	0.1216	-0.0396	578.44
		(5.38)*	(3.00)*	(1.45)	(3.72)*	(-1.22)	
ETF32	952	0.0407	-0.0040	0.0275	0.0504	0.0525	372.50
		(1.25)	(-0.12)	(0.85)	(1.55)	(1.61)	
ETF33	952	0.1180	0.0716	0.0424	0.0540	-0.0561	139.15

		(3.63)*	(2.19)*	(1.30)	(1.66)	(-1.73)	
ETF34	952	0.1743	0.0975	0.0789	0.1780	-0.0337	1106.55
		(5.36)*	(3.00)*	(2.43)*	(5.48)*	(-1.04)	
ETF35	952	0.1476	0.0738	0.0190	0.1032	-0.0409	292.12
		(4.54)*	(2.26)*	(0.58)	(3.16)*	(-1.26)	
ETF36	952	-0.0758	-0.0167	-0.0634	0.0866	0.0350	1069.42
		(-2.33)*	(-0.51)	(-1.96)*	(2.67)*	(1.08)	
ETF37	952	0.1697	0.0349	0.0447	0.1226	-0.0384	93.92
		(5.23)*	(1.07)	(1.37)	(3.75)*	(-1.18)	
ETF38	952	-0.1484	-0.0066	0.0035	-0.0357	-0.0317	366.14
		(-4.57)*	(-0.20)	(0.11)	(-1.09)	(-0.98)	
ETF39	952	0.2593	0.0880	0.0979	0.1216	-0.0627	124.03
		(7.99)*	(2.64)*	(2.94)*	(3.65)*	(-1.93)	
ETF40	952	0.1808	0.0397	0.0685	0.1728	-0.0255	64.70
		(5.56)*	(1.22)	(2.11)*	(5.31)*	(-0.79)	
ETF41	952	-0.0631	0.0283	0.0211	-0.0002	0.0220	1033.71
		(-1.94)	(0.87)	(0.65)	(-0.01)	(0.68)	
ETF42	952	0.6181	0.2170	0.0258	0.0309	-0.0309	339.23
		(19.00)*	(5.68)*	(0.67)	(0.81)	(-0.95)	
ETF43	952	-0.1095	-0.0092	0.0048	-0.0068	-0.0416	2723.21
		(-3.37)*	(-0.28)	(0.15)	(-0.21)	(1.28)	
ETF44	952	0.8573	-0.0608	0.0788	0.0414	-0.0759	650.12
		(26.40)*	(-1.42)	(-1.85)	(0.97)	(-2.34)*	

Notes: Panel B shows the first-order to fifth-order autocorrelation coefficients during 01/01/2007 and 31/08/2010, the figure in ( ) denotes t-value, * denotes statistical significance at 5% level.

3.3.2 Sentiment Proxies

We examine the impact of two types of sentiment proxies. Gemmill and Thomas (2002), Shleifer and Summers (1990), DeLong, Shleifer, Summers and Waldman (1990) and Lee, Shleifer and Thaler (1991) all examine investor sentiment using indirect measures of investor sentiment. These measures include closed-end fund discounts, odd-lot sales and mutual fund redemptions. With regard to direct measures of investor sentiment, Brown and Cliff (2004, 2005), and Han (2006) are amongst the first to use investor survey data, while Lemmon and Portniagina (2006) employ monthly data from the University of Michigan Index of Consumer Sentiment poll. Baker and Wurgler (2006, 2007) propose the combination of several underlying proxies into a composite index of sentiment.

One popular indirect proxy for investor sentiment is the option market. Baker and Wurglur (2006) suggest that options prices rise when the value of the underlying asset has greater expected volatility, and options pricing models such as the Black–Scholes formula can be inverted to yield implied volatility as a function of options prices. The Market Volatility Index (“VIX”), which measures the implied volatility of options on the Standard and Poor 100 stock Index, is often called the “investor fear gauge” by practitioners. Wang, Keswani and Taylor (2006) propose the use of put-call trading volume and open interest ratios as a sentiment indicator. In the light of this, and taking into account data availability, in this study we focus on the option market. The daily sentiment indicators used comprise the Euronext.liffe London put–call ratio and implied volatility index.

According to Wang, Keswani and Taylor (2006), the put–call trading volume ratio (PCV) is a measure of market participants' sentiment derived from options, and equals the trading volume of put options divided by the trading volume of call options. When market participants are bearish, they buy put options either to hedge their spot positions or to speculate bearishly. Therefore, when the trading volume of put options becomes large in relation to the trading volume of call options, the ratio goes up, and vice versa.

Another measure of the put–call volume ratio uses the open interest of options instead of trading volume. This ratio can be calculated on a daily basis using the open interest of options at the end of the day, or on a weekly basis using the open interest of options at the end of the week. This might be a preferred measure of sentiment as it may be argued that the open interest of options is the final picture of sentiment at the end of the day or the week, and is therefore likely to have better predictive power for volatility in subsequent periods. Therefore, this measure of sentiment is also used. The put–call ratio calculated in this way is labelled the PCO ratio.

Table 3.2 Summary Statistics

Variable	Mean	St. Dev	Skew.	Kurt.	Autocorrelation				
					lag1	2	3	4	5
PCV	0.7655	0.6388	3.1713	16.3216	0.2685	0.1025	0.0897	0.0545	0.0692
					(8.31)*	(3.07)*	(2.68)*	(1.62)	(2.13)*
ΔPCV	0.0011	0.7264	-0.6600	13.9407	-0.7017	-0.5509	-0.4414	-0.3594	-0.2909
					(-23)*	(-15.4)*	(-11.8)*	(-10.1)*	(-9.53)*
PCO	0.7556	0.2078	0.6635	-1.0424	0.8514	0.0963	0.0927	-0.0253	-0.0187
					(26.2)*	(2.26)*	(2.17)*	(-0.599)	(-0.584)
ΔPCO	-3.86901E-05	0.0159	-0.1906	33.6778	-0.142663	-0.0454759	0.040251	-0.0041	-0.05144
					(-4.41)*	(-1.39)	(1.23)	(-0.125)	(-1.62)

Notes: Table 3.2 reports the descriptive statistics different sentiment proxies and their autocorrelation from first lag to fifth lag.

Table 3.2 contains summary statistics of all the sentiment variables discussed in this section. The levels of all the sentiment indicators display a skewed and leptokurtic pattern, whilst the first differences of all the indicators are also skewed and leptokurtic. None of the sentiment indicators has substantial positive autocorrelations; the first differences of PCV have significant negative lag autocorrelations, while those for ΔPCO have lag autocorrelations that are negative, but not significant.

Figure 3.2 shows the trend comparison between the two sentiment measures. We find that PCV has a substantial positive correlation with PCO, but is more volatile; PCO tends to be stable over the whole sample period.

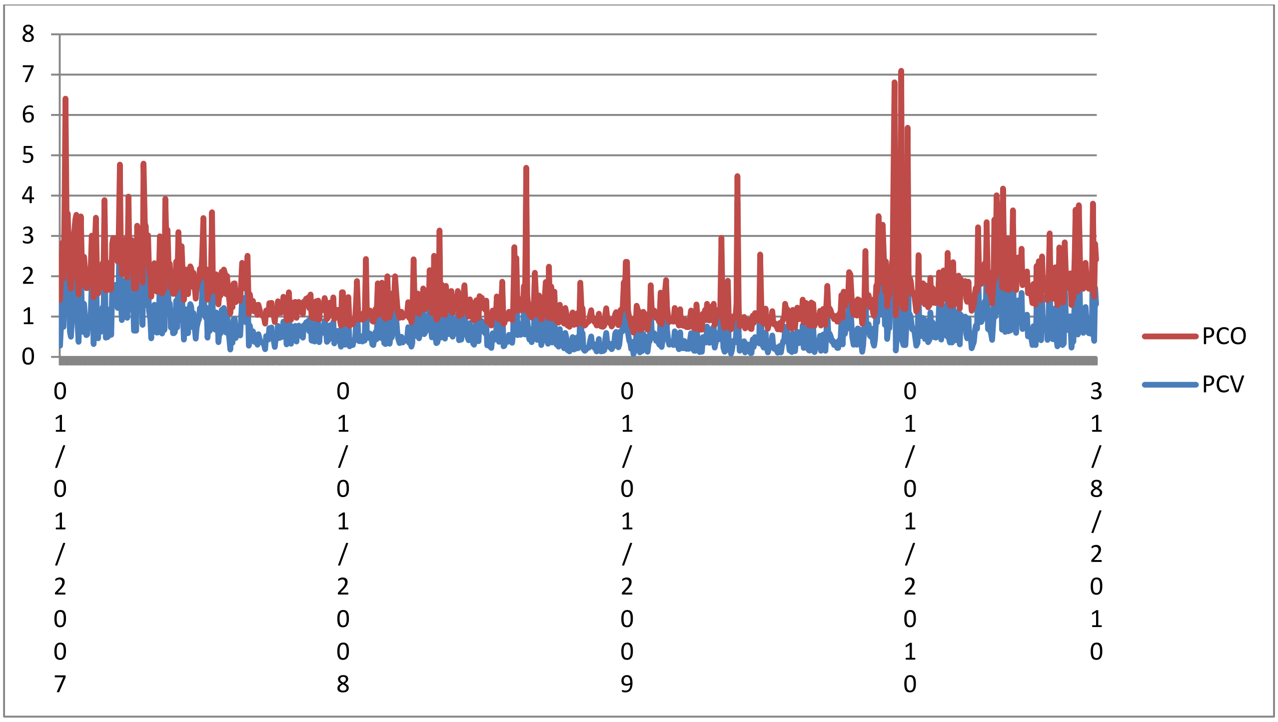


Figure 3.2 Trends of PCV and PCO measures

3.4 Methodology

One way to investigate the predictive power of sentiment and other factors for the ETF mispricing is to run the regression to determine whether there exists any relationship among them. First, we try to discover whether any other factors impact on the ETF price. Then, we investigate whether the sentiment has an important effect on the ETF mispricing.

Following Ackert and Tian (2008), we use the natural logarithm of market value, the natural logarithm of home market trading volume, home market illiquidity (AIM), and momentum as the explanatory variables, and the fund premium as the explained variable. The fund premium is defined as the difference between the ETF price and the fund's net asset value, divided by the net asset value. MV is the natural logarithm of ETF market capitalization. VOL is the natural logarithm of pound trading volume. Amihud's illiquidity measure (AIM) is the square root of the ratio of daily return and pound volume, and momentum (MOM) is measured by the continuous growth (percentage change) in the fund's NAV. Therefore, our regression is based on the following equation:

$$PREM_{it} = \alpha_{it} + \beta_{i0} SENT_t + \beta_{i1} MV_{it} + \beta_{i2} VOL_t + \beta_{i3} AIM_t + \beta_{i4} MOM_{it} + \varepsilon_{it}$$

(3.1)

3.5 Empirical Results

3.5.1 Preliminary Daily Results

Panel A of Table 3.3 presents the result of using PCV as proxy for investor sentiment. From this panel, we can observe that sentiment has a significant effect on the ETF premiums: 27 out of 44 funds have significant loadings at different levels, suggesting that sentiment may be an important factor in the UK ETF mispricing. For the market value variable, we find a significant relationship to the fund premiums in half (22 out of 44) the ETFs of the sample. There seems to be a negative relationship between the liquidity and the fund premium, since the market trading volume has a negative coefficient while the illiquidity factor has a positive coefficient; both have significant effect on ETFs, a result consistent with Ackert and Tian

(2008) finding in the US market, and supportive of Brennan and Subrahmanyam (1996) and Amihud (2002) arguments that more liquidity increases the fund price so that the fund premium would be lower. Therefore, we expect a positive relationship between AIM and fund premiums. Furthermore, when we check the result for momentum factor, we find that past price changes in NAVs (momentum) have significant effect on premium in almost all the regressions, which indicates that the past information is not fully reflected in current UK ETF prices, and that the past price changes can be persistent over time

Panel B of Table 3.3 shows the result of using the put-call ratio as proxy for investor sentiment. Once again, the result shows that sentiment has a significant effect on the ETF premiums. In this panel, 26 out of 44 funds have significant loadings at different levels, which are very close to our findings with PCV as proxy, suggesting that sentiment plays a key role in explaining the ETF mispricing. Regarding the market value variable, we find a significant relationship to fund premiums in half (22 out of 44) the ETFs of the sample, the same result as in Panel A. Moreover, the relationship between the liquidity and the fund premium has the same pattern as our previous findings. Similarly, the result for momentum factor shows that past price changes in NAVs (momentum) have significant effect on premium in almost all the regressions, which indicates that the past information is not fully reflected in current UK ETF prices, and that the past price changes can be persistent over time.

Table 3.3 Panel A

The time-series regression results for 44 ETFs using the PCV proxy

	Intercept	SENT	MV	VOL	AIM	Momentum	Adj.R^2
Model :	$PREM_{it}=\alpha_{it}+\beta_{i0}SENT_t+\beta_{i1}MV_{it}+\beta_{i2}VOL_t+\beta_{i3}AIM_t+\beta_{i4}MOM_{it}+\varepsilon_{it}$						
ETF1	7.26**	0.0131**	-0.847**	-0.473**	2.85	9.51**	0.154
ETF2	21.1**	0.0327**	1.46**	-2.59**	30.6**	-0.449	0.283
ETF3	2.17	0.00348**	0.368*	-0.273	5.78**	4.72**	0.0357
ETF4	1.84	-0.00179	-0.248**	-0.128	3.841	3.27**	0.0265
ETF5	82.9**	0.0324**	-1.33**	-8.24**	84.4**	73.5**	0.305
ETF6	-3.67	0.00917**	0.0295	0.355	-3.64	8.65**	0.0285
ETF7	7.79*	0.00412*	-0.0406	-0.793*	9.68*	3.64	0.0135
ETF8	7.69**	-0.00593**	-0.0315	-0.759**	-10.6**	-10.8**	0.0244
ETF9	2.76	-0.000649	0.0157	-0.283	-3.04	-6.10*	0.00506
ETF10	-3.83	0.000777	-0.0614	0.391	9.60**	12.0**	0.0393
ETF11	3.21	-0.00569**	0.0898**	-0.331*	-5.20**	1.33	0.0303
ETF12	3.19	-0.00322**	0.0259	-0.321	4.43	4.04	0.0101
ETF13	-0.535	-0.00215	0.0361	0.0558	0.151	4.70*	0.00252
ETF14	-2.52	-0.000177	0.0312	0.260	1.56	-6.91	0.00766
ETF15	4.80	-0.00635**	0.0377	-0.481	-6.88*	10.4**	0.0192
ETF16	20.9**	-0.00169	-0.739**	-1.97**	26.1**	71.6**	0.244
ETF17	-10.8**	-0.00716**	1.799**	0.566	-9.59*	7.72**	0.0826
ETF18	5.34**	-0.00293*	0.0904	-0.545**	-9.58**	5.76**	0.0369
ETF19	0.847	-0.00687**	-0.165	-0.0124	2.49	4.94**	0.0262
ETF20	7.38**	0.00175	0.267**	-0.807**	12.8**	3.96**	0.0426
ETF21	3.08*	-0.00199*	-0.0968**	-0.299	2.90	7.46**	0.0481
ETF22	3.02*	-0.00186	0.176	-0.326*	-4.69*	5.26**	0.0255
ETF23	33.8**	-0.0326**	-0.412*	-3.29**	41.1**	70.3**	0.233

ETF24	12.9*	-0.00450	-0.120	-1.28*	-13.6	5.82	0.00613
ETF25	4.26	-0.0137*	-0.0465	-0.358	-1.3	47.2**	0.0919
ETF26	-15.5**	0.0138**	-0.126**	1.54**	29.1**	0.00256	0.280
ETF27	7.42**	0.00267	0.647**	-0.860**	14.3**	1.67	0.0165
ETF28	12.0**	-0.00395	0.156	-1.22**	23.0**	5.06**	0.0468
ETF29	-13.8**	0.00354	0.801**	1.24**	12.9**	6.55*	0.0208
ETF30	9.58	0.0126**	1.39**	-1.40*	18.1*	185.0**	0.727
ETF31	49.9**	-0.0285**	-0.404**	-4.95**	59.0**	80.1**	0.236
ETF32	-4.81	-0.00216	0.422**	0.379	10.4	6.44	0.0142
ETF33	18.1**	-0.00138	0.151	-1.90**	-19.8**	5.16**	0.0257
ETF34	25.9**	-0.0182**	-0.116	-2.57**	27.9**	15.3**	0.0534
ETF35	-3.98*	0.00679**	-0.0448	0.399*	7.32**	6.63**	0.0478
ETF36	10.0*	0.00344	0.737	-1.26**	17.0**	183.0**	0.695
ETF37	32.3**	-0.0387**	-0.348	-3.14**	41.0**	62.8**	0.270
ETF38	6.06	-0.00354	0.0557	-0.591	11.8	23.4**	0.0298
ETF39	42.7**	-0.0545**	-1.28**	-3.96**	51.5**	70.8**	0.247
ETF40	12.5*	-0.0138**	-0.369**	-1.15	-19.5**	22.7**	0.0588
ETF41	17.6**	-0.00907**	-0.450**	-1.63**	19.1**	-8.99	0.0213
ETF42	93.9**	-0.0247**	-0.753**	-9.39**	-94.1**	96.3**	0.185
ETF43	-2.63	-0.000177	0.0650	0.272	-0.344	37.1**	0.0572
ETF44	-176.0**	0.0383**	14.0**	14.0**	171.0**	30.6*	0.0352

Notes: This table reports the time series relationship between the daily premiums on 44 ETFs NAV, changes in the put-call trading volume ratios, MV is the natural logarithm of ETF market capitalization, VOL is the natural logarithm of pound trading volume. AIM is the square root of the ratio of daily return and pound volume, MOM is measured by the continuous growth (percentage change) in the fund's NAV. **Denotes statistical significance at the 5% level.* Denotes statistical significance at the 10% level.

Table 3.3 Panel B

The time-series regression results for 44 ETFs using the PCO proxy

	Intercept	SENT	MV	VOL	AIM	Momentum	Adj.R^2
Model :	$PREM_{it} = \alpha_{it} + \beta_{i0} SENT_t + \beta_{i1} MV_{it} + \beta_{i2} VOL_t + \beta_{i3} AIM_t + \beta_{i4} MOM_{it} + \varepsilon_{it}$						
ETF1	14.6**	-0.517**	-1.07**	-1.04**	10.8**	9.98**	0.101
ETF2	15.3**	-2.30**	0.574**	-1.39**	20.1**	-1.28*	0.180
ETF3	5.12**	0.136	0.027	-0.521**	0.871**	4.808**	0.030
ETF4	3.17	0.298**	0.308**	-0.295	5.64**	-3.21**	0.049
ETF5	76.0**	-3.67**	-1.68**	-6.88**	70.8**	0.909**	0.022
ETF6	0.785	-1.67	0.105	-0.783	-0.971	-11.6**	0.124
ETF7	3.21*	-1.20**	-1.01	-3.18*	-3.23*	-8.87*	0.082
ETF8	1.52**	0.333*	-0.582	-1.50**	1.83**	-11.8**	0.126
ETF9	1.57	0.382	0.00164	-1.58	-1.48	-14.7*	0.183
ETF10	-1.39**	-1.50**	-1.68**	1.43**	3.22**	-2.72**	0.037
ETF11	0.072	0.730**	1.35**	-0.152	0.298	-7.84*	0.060
ETF12	0.725	0.325*	0.761	-0.758	0.754	-5.97*	0.033
ETF13	0.00732	1.00*	0.350	-0.0218	0.104	-6.60	0.041
ETF14	-0.401	0.913*	0.541	0.414	0.0756	-7.66*	0.058
ETF15	0.300	0.885	0.563	-0.342	-0.403	-3.02**	0.006
ETF16	3.16	-0.825**	-3.31**	-2.85	2.56	-1.18**	0.032
ETF17	-3.74**	0.525	4.19**	2.80*	0.445	-4.13**	0.082
ETF18	2.85**	0.748**	2.40**	-2.89**	-3.64**	-4.19**	0.032
ETF19	-0.120	1.08**	0.308	0.0885	-0.0974	-6.77**	0.044
ETF20	4.65**	-0.554	3.06**	-4.73**	5.51**	-4.65**	0.051
ETF21	0.597**	-0.766**	-2.71**	-0.509**	0.0603**	-4.75**	0.033
ETF22	1.52**	1.36**	2.51	-1.73**	1.80**	-8.22**	0.068
ETF23	1.06	-0.256	-0.633	-1.04	-0.566	0.606**	0.003
ETF24	1.73*	0.489	-1.21	-1.71*	-1.08	-17.6	0.244
ETF25	-2.15	0.299**	1.80	2.16*	1.40	-47.9**	0.706

ETF26	-5.55**	-3.54**	0.357**	5.52**	9.26**	-1.94	0.166
ETF27	3.05	2.39**	1.45**	-2.88	3.61*	-1.52	0.018
ETF28	3.16**	0.553	1.80	-3.28**	5.06**	-4.39**	0.055
ETF29	-3.23**	0.564	3.57**	2.94**	2.38**	-4.35	0.031
ETF30	1.48	0.116**	2.10**	-1.83	-1.98	-2.08**	0.008
ETF31	3.12**	1.29	-1.07	-3.16**	-2.93**	1.42*	0.008
ETF32	-0.871	0.113	2.02*	0.713	1.65	-12.6*	0.148
ETF33	4.13*	0.381	0.733**	-4.19	-3.28	-3.32	0.026
ETF34	2.20	0.660	0.314	-2.25	-1.70	9.29**	0.088
ETF35	0.291**	-1.31**	-0.608	-0.254**	0.515**	-3.26**	0.011
ETF36	0.742	0.219**	1.51	-1.37	1.39	-8.90**	0.075
ETF37	0.602	1.08	0.216*	-0.629	0.604	-1.87**	0.005
ETF38	1.17	0.144	0.292	-1.16	1.58	-31.4**	0.510
ETF39	1.76**	1.14*	0.778	-1.79**	1.64**	0.167**	0.004
ETF40	0.385	0.125**	-1.58*	-0.259	0.838	4.09**	0.019
ETF41	1.92**	1.34	-3.18**	-1.76**	1.55*	-4.73*	0.031
ETF42	9.92**	-0.530**	-4.25**	-9.92**	7.55**	-1.98**	0.120
ETF43	-0.741	0.152**	0.695	0.742	0.309	-31.8**	0.514
ETF44	-4.95**	0.615	4.98**	4.36**	4.06**	-10.8*	0.129

Notes: This table reports the time series relationship between the daily premiums on 44 ETFs NAV, changes in the put-call open interest ratios, MV is the natural logarithm of ETF market capitalization, VOL is the natural logarithm of pound trading volume. AIM is the square root of the ratio of daily return and pound volume, MOM is measured by the continuous growth (percentage change) in the fund's NAV. **Denotes statistical significance at the 5% level.* Denotes statistical significance at the 10% level

3.5.2 Other Sentiment Proxies

Gemmill and Thomas (2002), Shleifer and Summers (1990), DeLong, Shleifer, Summers and Waldman (1990) and Lee, Shleifer and Thaler (1991) all examine investor sentiment using what are considered indirect measures of investor sentiment. These measures include closed-end fund discounts, odd-lot sales and mutual fund redemptions. In the above sections, we have examined the proxies indicated by the option market, which can also be classified as indirect measures of investor sentiment. In contrast, Brown and Cliff (2004, 2005), and Han (2006) use investor survey data, which can be classified as direct measures of investor sentiment. They use retail and INST data to indicate the percentages of investors who feel bullish and bearish about the market, and are provided on a weekly basis. Lemmon and Portniagina (2006) use the University of Michigan Index of Consumer Sentiment poll, which is a monthly direct measure of investor sentiment. Given that two different types of measure may offer the most efficient means of testing the feelings and expectations of investors, this study employs both direct and indirect measures of investor sentiment.

There are two main consumer confidence surveys carried out across the UK market which can be used as the proxy of investor sentiment. First, the GFK NOP Consumer Confidence Barometer has been running in the same format across Europe since the early 1970s, and in the UK since June 1995. The survey is carried out on a monthly basis on behalf of the European Commission, which sponsors the same research in all European Union member countries. Each month the survey tracks changes in personal finance, general economic situation, inflation, unemployment, current purchasing climate, consumer spending and saving. Quarterly research tracks car purchasing, home purchasing and home improvements. Results from The Consumer Confidence Barometer are available as either a 6-monthly or annual subscription, running from May to April.

Second, the Nationwide Building Society Consumer Confidence survey is conducted for the Nationwide by TNS. This survey was started in May 2004. Each month 1,000 adults are interviewed, with the sample structured to be nationally representative of all adults in term of age, sex and socio-economic group. Data are available monthly. The questions asked are based on those asked by the Conference Board, tailored to UK conditions, and the Index is based on responses to 5 questions regarding respondents' appraisal of current economic conditions, economic conditions six months hence, current employment conditions, employment conditions six months hence, and their total family income six months hence. As can be seen from Figure 3, although the two surveys use different methodologies, the trend of the consumer confidence is almost the same.

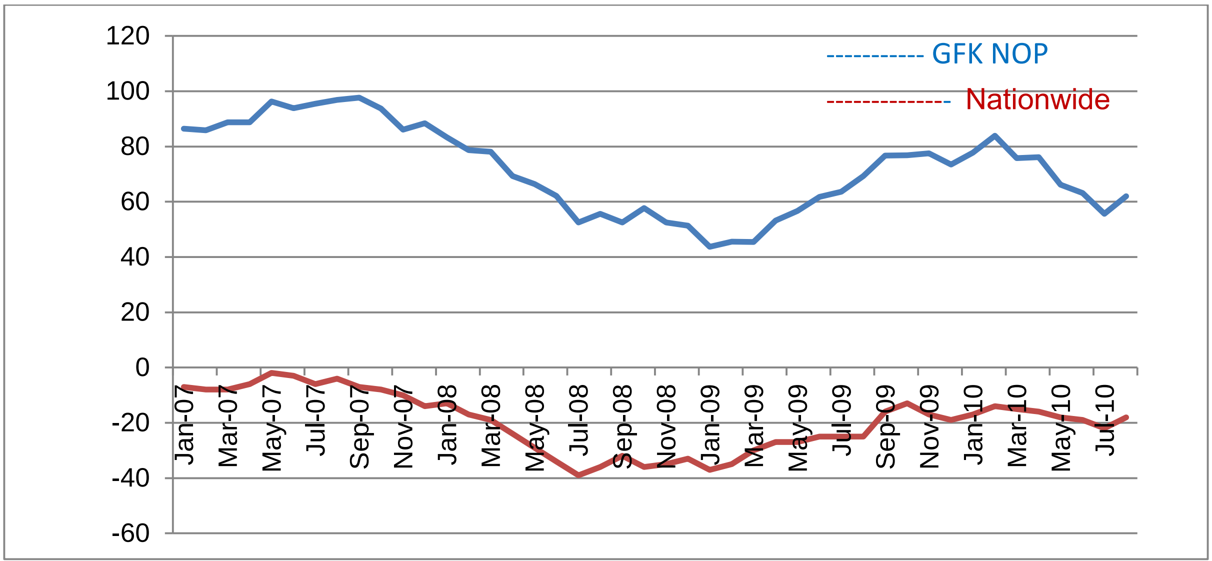


Figure 3.3 Consumer Confidence Indices

Since the two surveys are provided on a monthly basis, we employ monthly data spanning the period from January 2007 to December 2010. This sample period ensures that we obtain sufficient fund information and observations.

3.5.3 Estimation of Sentiment Betas

In this section, we add the Fama-French three factors, market, size and book-to-market, and the momentum factor, which together comprise Carhart's (1997) four factors. Therefore, the second model is designed to test the relationship between the sentiment in ETF price premium and Carhart's (1997) four factors. The model can be presented as:

$$PREM_{it} = \alpha_i + b_i R_{mt} + s_i SMB_t + h_i HML_t + w_i WHL_t + \beta_i \Delta SENT_t + \varepsilon_{it} \quad (3.2)$$

Where

$PREM_{it}$ = fund premium, defined as the difference between the ETF price and the fund's net asset value, divided by the net asset value

R_{mt} = the return of market portfolio m in month t minus risk free rate

SMB= the return on a portfolio of small stocks minus the return on a portfolio of big stocks (small minus big in terms of size)

HML= the return on a portfolio of value stocks minus the return on a portfolio of growth stocks (high minus low in terms of B/M)

WML= the return on a portfolio of winner stocks minus the return on a portfolio of loser stocks (winners minus losers in terms of return)

$\Delta SENT$ = standardized sentiment factor proxy, change of consumer confidence index

It is documented that betas obtained from the model could be statistically imprecise and may contain a fair amount of statistical noise due to a relatively low number of degrees of freedom and other statistical problems associated with the use of individual fund premiums. Previous studies on the securities market have developed some approaches to solve this problem. One such approach is based on portfolio formation, because if the errors in the individual security betas are substantially less than perfectly positively correlated, the betas of portfolios can be much more precise estimates of true betas. However, there is always a question regarding the most appropriate portfolio formation procedure, as it is subject to data-mining concerns. For example, Daniel and Titman (2005) point out that forming portfolios on the basis of common variables such as size and book-to-market (BM) is likely to wash out any variation in factor loadings that are independent of size and BM, leading to low test power to reject the null. Also, assigning portfolio betas to the securities in this portfolio disregards the fact that true betas are not the same for all stocks in a portfolio.

The other common and useful way of reducing noise in the beta estimates is to “shrink” the usual estimates to a reasonable value, a procedure often referred to as the Bayes-Stein adjustment. The “shrinkage” estimate of beta is the weighted average of the usual OLS estimate and of the shrinkage target. Shrunk betas can be justified as so-called “Bayesian” estimators, in that they reflect not only current data but also prior knowledge or judgment. Bayesian estimators have solid axiomatic foundations in statistics and decision theory, unlike many other estimators commonly used by statisticians (see Vasicek, 1973; Blume, 1971, 1973; Scholes&Willams, 1977; Jorion, 1986). For instance, Chan et al.’s (1992) results indicate that such robust “Bayesian” estimators (including ones that use the information contained in the prior cross-section) are superior to more usual OLS estimates in terms of precision. The "shrinkage" approach is adopted in this paper.

Specifically, in the first stage, sentiment betas are estimated separately for each stock using the traditional rolling OLS regression approach. The four-year period monthly regressions are run for each ETF. Priors are formed using the empirical Bayesian approach, that is, the prior density of sentiment betas is assumed to be normal with the mean β_t^{prior} and variance

$$\sigma^2_{prior,t}\ ;\ \sigma^2_{prior,t} = \frac{1}{N_t}\sum_i (|\beta_{i,t}| - \beta_t^{prior})^2 \beta_{SENT,i}\ \beta_{i,t} \sim \mathrm{N}\,(\beta_t^{prior}\ ,\ \sigma^2_{prior,t}) \quad (1)$$

Where the prior mean is an average of the *absolute* values of cross-sectional betas from the previous period and the prior variance is the cross-sectional variance of the last available cross-section of absolute values of sentiment betas. The posterior sentiment betas are obtained as follows:

$$\beta_{i,t+1}^{posterior} = \frac{\sigma^2_{prior,t}}{\sigma^2_{prior,t} + \sigma^2_{\beta,t+1}} \times |\beta_{i,t+1}| + \frac{\sigma^2_{\beta,t+1}}{\sigma^2_{\beta,t+1} + \sigma^2_{prior,t}} \times \beta_t^{prior} \qquad (2)$$

$$\beta_t^{prior} = \frac{1}{N_t}\sum_i |\beta_{i,t}|\ ,\ \sigma^2_{prior,t} = \frac{1}{N_t}\sum_i (|\beta_{i,t}| - \beta_t^{prior})^2$$

Where N_t is the number of stocks used in estimation at time t, $\beta_{i,t+1}^{posterior}$ is the shrinkage estimate of sentiment beta, henceforth referred to as "sentiment betas", $\sigma^2_{\beta,t+1}$ is the sampling variance of the OLS estimator computed in the period t+1 and $\beta_{i,t+1}$ is the standard OLS regression coefficient $\beta_{SENT,i}$ from model (3.2), henceforth referred to as "original sentiment betas". The intuition of formula (2) is straightforward: less precise betas get shrunk towards the prior with the weight reflecting the estimate's precision relative to the precision of the prior. The advantage of the shrinkage approach compared to the portfolio approach is that the standard error of each sentiment beta is taken directly into account.

Table 3.4 Panel A Summary statistics for the time-series averages of sentiment betas

Extreme observations

Lowest			Highest		
Value	Company	Ticker	Value	Company	Ticker
-0.0441	USD COPORATE BD.	LQDE	0.0797	STOXX EURO 50	EUN
-0.0166	MSCI EASTERN EUROPE 10/40	IEER	0.0416	MSCI TURKEY	ITKY
-0.0134	FTSE/MACQUARIE GLB.INFR.100	INFR	0.0410	MSCI TAIWAN	ITWN
-0.0103	FTSE UK ALL STOCKS GILT	IGLT	0.0407	FTSE EPRA/NAREIT US PR.FD	IUSP
-0.0098	XINHUA/CHINA 25	FXC	0.0398	MSCI JAPAN	IJPN

	Descriptive statistics		Quantiles	
	N	44	100% Max	0.0797
	Mean	0.0085	90%	0.0355
	Median	0.0056	75%Q3	0.0164
	Std	0.0204	50%Median	0.0056
	Skewness	0.8593	25%Q1	-0.0058
	Kurtosis	2.2019	10%	-0.0103
	Interquartile Range	0.0220	0%Min	-0.0441

Table 3.4 Panel B Summary statistics for the time-series averages of shrunk sentiment betas

Extreme observations

Lowest			Highest		
Value	Company	Ticker	Value	Company	Ticker
0.0064	EUR GOVERNMENT BOND 1-3	IBGS	0.0566	STOXX EURO 50	EUN
0.0072	EURO INFLATION LINKED BOND	IBCI	0.0342	USD COPORATE BD.	LQDE
0.0072	FTSE UK DIV.PLUS	IUKD	0.0326	MSCI TURKEY	ITKY
0.0074	DJ ER.STOXX GROWTH	IDJG	0.0322	MSCI TAIWAN	ITWN
0.0075	ISHARES ER.GVT.BD.15-30	IBGL	0.0321	FTSE EPRA/NAREIT US PR.FD	IUSP

Descriptive statistics		Quantiles	
N	44	100% Max	0.0566
Mean	0.0161	90%	0.0321
Median	0.0122	75%Q3	0.0181
Std	0.0101	50%Median	0.0122
Skewness	1.8815	25%Q1	0.0097
Kurtosis	4.0892	10%	0.0075
Interquartile Range	0.0080	0%Min	0.0064

Tables 3.4a and 3.4b present the summary statistics/empirical distributions of original and Bayes-Stein sentiment beta estimates. The negative original sentiment betas indicate those contrarian sentiment traders who buy the securities when sentiment is low and sell when it is high, while the positive sentiment betas indicate momentum traders, who buy the securities when the sentiment is high and vice versa. Additionally, we can see that the distribution of the original betas is relatively symmetric around zero, although the mean of the distribution as zero is rejected at 1% level using standard t-test. This suggests that the impact of investor

sentiment on the UK market is non-zero action, and the two kinds of traders (contrarian and momentum) do not seem to cancel each other out when the market is considered as a whole.

3.5.4 Sentiment Beta and Firm Characteristics

Table 3.5 Firm characteristics

	Beta	Size	Market Beta	SMB	HML	Yield	Age	6m returns	Premium
1	0.0071	2673	0.973	-0.137	0.118	0.048	112	0.068	0.079
2	0.0076	1792	1.022	-0.076	0.090	0.041	110	0.088	0.093
3	0.0097	1537	1.033	-0.023	0.050	0.037	104	0.093	0.149
4	0.0103	1045	1.031	0.048	0.052	0.027	97	0.094	0.174
5	0.0109	973	1.046	0.098	-0.009	0.023	94	0.105	0.265
6	0.0120	842	1.090	0.125	0.021	0.018	86	0.106	0.278
7	0.0136	821	1.068	0.204	0.002	0.016	82	0.112	0.302
8	0.0164	766	1.118	0.228	-0.051	0.014	73	0.120	0.376
9	0.0241	529	1.109	0.373	-0.094	0.014	68	0.124	0.390
10	0.0365	496	1.134	0.492	-0.080	0.012	62	0.128	0.410

Table 3.5 presents the relationship between sentiment beta and firm characteristics. It reports the time-series averages of cross-sectional means. Size is the market value of the ETF (in millions of pounds). Market/SMB/HML betas are the value-weighted averages of the corresponding betas of ETFs. Yield is the average distribution yield since inception. Age is

the number of months since the inception date of the individual ETF. Past 6 Months return is the cumulative return over six months prior to the beginning of the month.

Comparison of book-to-market ratios across the deciles suggests that sentiment is relatively more pronounced in low B/M ETF underlying assets, which implies that effects of investor sentiment are more pronounced not in extreme growth ETFs but rather in moderate growth ETFs. Further evidence on the relation between sentiment beta and growth/value comes from the portfolios' HML loadings: decile 1 (lowest sensitivity) has an HML beta of 0.118, whereas decile 10 (highest sensitivity) has an HML beta of only -0.080. The result shows that sentiment change is higher among glamour ETFs, which is consistent with findings by Frazzini and Lamont (2006), who report that high sentiment stocks tend to be stocks with low book-to-market ratios. It also supports evidence presented in Elsewarapu and Reinganum (2004), who find that annual excess returns on the stock market index are negatively related to the returns of glamour stocks in the previous 36-month period, whereas neither returns of value stocks nor aggregate stock market returns, net of glamour stock effects, have any predictive power. This result is, however, in contrast to Baker and Wurgler (2006), who do not find any significant difference in future returns of growth and distressed (value) stocks following periods of particularly high or low investor sentiment.

More sentiment-sensitive ETFs have lower distribution yields. They fall monotonically from 4.8% to 1.2% as we move from decile 1 to decile 10. The result also provides evidence that more profitable ETFs are more subject to shifts in investor sentiment, and they have more recent inception date. Further supporting evidence for our previous hypothesis that investor sentiment can be a factor of ETF price premium comes from analysing the relationship between the premiums and sentiment beta. From the table, we may conclude that higher sensitivity to shifts in investor sentiment potentially arises due to the fact that certain ETF characteristics make it difficult for investors to value that ETF, resulting in greater differences of opinion among investors regarding the fair value. As a result of this, the larger premium appears.

3.5.5 Results for all ETFs

Table 3.6

Panel regression for all 44 ETFs					
	SENT	MARKET	SMB	HML	WHL
Coefficient	0.0085	2.2131	-0.7456	0.8904	-0.2738
T-value	2.74**	2.00**	-0.6	0.99	-0.18

**Denotes statistical significance at the 5% level

The previous results show that the investor sentiment has a significant effect on the price premium of most of the individual ETFs. However, this evidence may not reveal the whole story. Our next step is to analyse whether or not the sentiment factor plays a key role in the whole ETF industry price premium, when we take all the ETFs into account and attempt to explain what factors are significant in explaining the premium.

Table 3.6 offers the results from panel data regression. We estimate the five dependent variables from equation (2): sentiment proxy (CCI index), market return, size, B/M ratio and momentum. The evidence shows that only sentiment and market factors have coefficient significant at 5% level; the ETF price premium seems unaffected by any other hypothesized factors. As we expected, the sentiment proxy has a positive coefficient, which suggests that when the investor sentiment is high, large fund premium appears, and vice versa.

3.6 Conclusions

Our objective in this paper is to discover whether investor sentiment can explain the UK exchange traded fund price premium. We address this issue by examining 44 iShare ETFs listed in the London Stock Exchange from 2006 to 2010. In order to test the hypothesis, we first construct a sentiment proxy from the derivative market as the option put–call trading volume ratio and the open interest ratio. The results provide evidence that this sentiment proxy has explanatory power for most individual ETF mispricing. Second, we develop a consumer confidence index sentiment proxy, obtained from the mainstream surveys and taken to individual fund level, defined as sensitivity of ETF price premiums to the changes of investor sentiment. Specifically, it is the coefficient in the time series regression of individual fund premiums on sentiment factor. The evidence shows that more sentiment-sensitive ETFs are smaller, younger and volatile stocks with low dividend yields. Finally, we take the whole industry into account and find that sentiment factor has incremental explanatory power and is positively related to the fund premium.

In general, all of these results present a consistent view which seems to indicate that investor sentiment significantly and positively impacts the ETF price premiums. When investors are very optimistic, they are more likely to miscalibrate, which leads to mispricing of the ETFs, and the premiums appear. When investors are pessimistic, the premiums shrink or discounts appear. Furthermore, different characteristics lead to the ETF firms exhibiting different levels.

CHAPTER 4

INVESTOR SENTIMENT AND REIT PRICE MOMENTUM

4.1 Introduction

A Real Estate Investment Trust (REIT) is a listed property company that manages a portfolio of real estate to earn profits for shareholders. It must have elected for REIT status and operate in accordance with REIT regulations, which are intended to ensure the company is primarily engaged in property investment, rather than in development or other non-property related activities. After paying a conversion fee, a REIT escapes corporation tax. It must pay out 90% of its property income to shareholders annually in the form of dividends.

The US Congress created REITs in 1960 as a way to give all investors the ability to invest in large-scale commercial properties. Since then, the REIT industry has been growing dramatically in both importance and size. Today, REITs own and operate commercial properties in every major metropolitan area across the US and in several international locations, and over the last few decades, REITs have outperformed most other major equity market benchmarks.[33] The fact that Standard & Poor has added REITs to its major indices indicates that the REIT industry has been recognized as a mainstream investment. There are now approximately 172 publicly traded REITs in the US, with a total equity market

[33] The compound annual return for Dec. 1971- Dec. 2012 for FTSE NAREIT All Equity REITs is 12.10%; whereas NASDAQ Composite is 8.19%, Dow Jones Industrials is 6.78%, S&P 500 is 9.99%. Source: NAREIT.

capitalization of over $600 billion. As such, REITs have become an important segment of the US economy and investment market.

The legislation laying out the rules for REITs in the United Kingdom was enacted in the Finance Act 2006 and came into effect in January 2007, when nine UK property companies converted to REIT status. British REITs have to distribute 90% of their income; they are close-ended investment trusts, which must be UK resident and publicly listed on a stock exchange recognized by the Financial Services Authority. Most UK REITs focus on the UK, although a few have European investments. This sort of specialization is a global characteristic of REITs, and reflects the diversity of legislation across countries.

Today, institutional and individual investors alike are attracted to REITs for their diversification qualities. Moreover, REITs are very tax efficient, as the property company pays no corporation or capital gains on the profits made from property investment. The major UK REITs are many times larger than most property unit trusts, and are transparent, as they are subject to continual market scrutiny. As REITs are all listed property companies, investments in them are generally liquid.

Stock price momentum has been extensively studied in the literature. Jegadeesh and Titman (1993) document that the US stock market yields a 12% annual return over the 30 years before their study using a momentum trading strategy. The authors suggest that these momentum returns are not a result of systematic risk of the securities. Chui, Titman and Wei (2003) also find significant momentum returns in Real Estate Investment Trusts (REITs) from 1982 to 2000, while Hung and Glascock (2008) find that REIT momentum returns are higher in up markets, and REIT winner portfolios have higher dividend to price ratios. Accordingly, it is reasonable to expect that investors' perceptions might affect the pricing and returns of REITs. However, of primary interest here is whether and under what circumstances the portion of these market participants' perception that is unrelated to risk, which serves as a proxy for irrational trader demand, has the ability to significantly affect REIT CEF price momentum. This paper sheds empirical light on whether investor sentiment affects the profitability of price momentum strategies in the REIT market.

4.2 Literature Reviews

4.2.1 Momentum in Stocks

Notwithstanding the preponderance of evidence supporting the superiority of the contrarian investment strategy, some researchers have adduced evidence in support of superior performance from the momentum investment strategy. Momentum in stock prices is well documented in the seminal work by Levy (1967), who concludes that profitable results are attainable by buying stocks that are historically comparatively strong. This is based on the belief that average stock returns are related to past performance and thus, to a certain extent, are predictable. Jegadeesh and Titman (1993) report a significant positive return using momentum trading strategy, which they define as a strategy that buys stocks that have performed well and shorts stocks that have performed poorly in the past periods, and holds the portfolio for 6 to 12 months. The authors find that this strategy yields a 12% annual return in the US stock market over the period from 1965 to 1990, and suggest that these momentum returns are not a result of systematic risk of securities. Asness (1995, 1997) investigates the performance of both value and momentum strategy in the stock market to show that these strategies are effective even after accounting for common value measures. In particular, they are most effective when the definition of momentum excludes returns over the most recent month.[34]

Cooper et al. (2004) find that the profits due to momentum strategies depend critically on the state of the market. Consistent with the DHS (1998) overreaction model, six-month momentum portfolio is profitable only following periods of market gains (up market state).[35] Moreover, the momentum profits increase when the lagged market return increases. They also reconfirm the findings of Lee and Swaminathan (2000) and Jegadeesh and Titman (2001) that momentum profits are reversed in the long run, as predicted by the overreaction theories. Most of the institutional money managers, especially in large growth and the large core domains, are momentum traders.

Sagi and Seasholes (2007) contribute to our understanding of momentum in a number of ways. First, they show that we can learn about future expected returns based on past returns and observable firm-specific attributes. Second, they suggest that momentum strategies carried out in high revenue volatility firms, low cost firms, and high market-to-book firms all produce greater profits than a traditional Jegadeesh and Titman (1993) strategy. Finally, in

[34] Defining the momentum strategy in this way avoids measurement problems induced by the bid-ask spread (Asness 1995).

[35] They define two states: (1) “UP” is when the lagged three-year market return is non-negative, and (2) “DOWN” is when the three-year lagged market return is negative.

accordance with Cooper et al. (2004), they argue that firms will exhibit higher momentum profits in up markets than they do in down markets.

Most recently, Daniel et al. (2012) investigate US stocks during the 978 months from July 1929 to December 2010. In their study, the returns generate an average monthly return in excess of 1.12% per month and an alpha of 1.70% per month with regard to the Fama and French (1993) three-factor model. The momentum strategy returns can result in a portfolio with a Sharpe Ratio of almost 0.28 per month when considered with the Fama and French (1993) three-factor returns. Nevertheless, inconsistent with previous studies, they argue that strategies also incur infrequent, but rather large, losses. In their sample of 978 months, there are 13 months with losses exceeding 20% per month.

The literature on the momentum strategy is predominantly focused on US individual equities. However, studies conducted in other contexts should also be considered. Rouwenhorst (1998) documents international momentum returns in a sample of 12 European countries over the period from 1980 to 1995.[36] The return patterns hold for both small and large firms, and exhibit stronger effect in small firms than in large firms. This is confirmed by Forner and Marhuenda (2003) in their analysis of the Spanish market, which has received little attention. Marshall and Cahan (2005) use Australian stock data to provide the first out-of-sample test of the 52-week high momentum strategy. After conducting a robustness test they find that the 52-week high momentum strategy is highly profitable in the Australian stock market. Their result is much larger than the equivalent return for this strategy in the US, a finding consistent

[36] In the sample, the twelve countries are: Austria, Belgium, Denmark, France, Germany, Italy, Netherlands, Norway, Spain, Sweden, Switzerland and the United Kingdom.

with George and Hwang (2004). Furthermore, the result is robust to the stocks of different size and liquidity and persists after risk-adjustment.

Several recent studies focus on the momentum effect in the emerging markets. Gonenc and Karan (2003) study the Istanbul Stock Exchange and find that a momentum portfolio performs better than a value portfolio. Jansen and Verschoor (2004) also provide evidence that growth premium exists in four emerging markets, namely the Czech Republic, Hungary, Poland, and Russia. Naranjo and Porter (2007) confirm the profitability of momentum trading strategies in both developed and emerging markets using data on almost 16,000 firms from 22 developed and 18 emerging markets over the period from 1990 to 2004. Muga and Santamaria (2007) contribute to the literature on the momentum effect at the international level; however, contrary to previous studies, they argue that momentum effects in emerging markets are notably smaller and weaker than in developed markets. Asness, Moskowitz and Pedersen (2013) examine value and momentum portfolios of individual stocks globally across four key equity markets: the US, the UK, continental Europe and Japan. They provide comprehensive evidence on the return premia to both value and momentum strategies in all four equity markets and a strong common factor structure among their returns. They further uncover that value and momentum returns correlate more strongly across asset classes than passive exposures to the asset classes, but value and momentum are negatively correlated with each other, both within and across asset classes.

4.2.2 Momentum in Housing and REITs

Case and Shiller (1989) study the housing data from 1970 to 1986 for Atlanta, Chicago, Dallas and San Francisco/Oakland, and show that the market for single family homes does not appear to be efficient. They conclude that there is substantial persistence through time in the change of real housing prices in these cities and that the excess returns of housing prices can be forecasted, because a change in real housing prices tends to be followed by changes in the same direction in the subsequent year. Their argument implies that there is a profitable trading rule in the house market for those people who can time the purchase of their homes. In a later work, Case and Shiller (1990) use quarterly indices of existing single family home prices to support their previous study. In this paper, looking at housing prices for Atlanta, Chicago, Dallas and San Francisco over the period 1970 to 1986 and estimating excess returns, they find that the price changes in one year will continue for more than one year in the same direction. Furthermore, they show that the ratio of construction cost to price, changes in adult population and increases in real per capita income are positively related to excess returns or prices changes over the subsequent year. Abraham and Hendershott (1993, 1996) document that the house price trends are localized phenomena; the lagged returns in the housing market in volatile coastal cities have double the explanatory power compared to the return in the inland cities. The areas where lagged returns have higher explanatory power are prone to form bubbles, and these areas have greater downward swings after the bubble bursts, particularly so in the Northeast and in California. The determinants of real house price appreciation can be divided into two groups: first, the growth in real income and real construction costs and changes in the real after-tax interest rate, which can explain changes in the equilibrium price; and second, lagged real appreciation and equilibrium real house price deviation.

Similarly, a number of studies investigate momentum at the real estate fund level, and find this to be significant. Chui et al. (2003) explore the REIT industry in detail, and test how the profitability of momentum changes over time. They suggest that REIT is a good industry to examine the intra-industry momentum, because it includes sufficient observations to estimate momentum returns, and because the structure of this industry changed around 1990, which is helpful to test the determination of momentum profit.[37] Their result shows that the momentum strategy generates 0.89 percent per month profit for the REIT sample during the 1983-1999 period; however, the magnitude of the post-1990 period momentum effect is quite large, whereas the momentum before 1990 is relatively small. Mulvey and Kim (2008) compare a long-only industry-level momentum strategy to active funds, and find that active fund performance patterns have been very similar since 1993; the similarity becomes stronger as time passes, and as funds performs better. They focus on industry-level data because of its better diversification compared with stock-level momentum strategy. The evidence shows that by adopting momentum rules, the mangers can improve their performance.

Kwame and lee (2009) investigate the relative return and risk of REIT value and momentum strategies. Their evidence illustrates that there is a significant value premium for the remaining holding period; in contrast, the momentum premium is attested to be statistically significant only for the yearly investment horizon. This suggests that value strategy in REIT investing is more profitable than momentum strategy. Their findings also imply that the return for value strategy cannot compensate for risk, but the momentum beta is found to be significant.

[37] There is a significant change in REIT after 1990 in terms of liquidity, size (see Clayton and McKinnon, 2000; Beneveniste, Capozza and Seguin, 2001; Chan, Erickson and Wang, 2003), investment portfolios (Capozza and Seguin, 1999, 2001a), ownership (see Capozza and Seguin, 2003) and capital structures and management strategies (see Capozza and Seguin, 1998, 2001b).

Beracha and Skiba (2011) examine whether there is return momentum in US residential real estate. Following Jegadeesh and Titman (1993), they construct long-short zero cost investment portfolios based on the lagged returns of 380 metropolitan areas. The result shows that the momentum returns of US residential real estate are statistically significant during the 1983-2008 sample periods; the average trading rule can earn up to 8.92 percent per year. Additionally, their finding indicates that the momentum effect in home prices is not impacted by the time period or geographical region.[38]

Feng et al. (2012) investigate in the REIT industry to examine the relation between the price momentum and post-earnings announcement drift (the incomplete reaction to earnings news). They document that the performance of momentum in REIT returns is well established, and that over the last two decades it has been increasing substantially compared to previous years. The drift is a unique aspect of equity REITs which has received a great deal of research attention in the recent literature, and this offers a good opportunity to study the potential industry level link between momentum and drift. Their result shows that the returns attributable to one tend to increase as the level of the other decreases, which suggests that there is a negative relation between REIT momentum and drifts. They conclude that the REIT drift has more pronounced effect on the future returns than does the momentum, and that it subsumes the payoffs to a momentum strategy at the industry-level.

[38] Nevertheless, they find that the momentum effect appears to be more pronounced in the West and Northeast regions during the 2004-2008 periods.

4.2.3 Why Momentum Strategies Work

There is a rich array of testable hypotheses supporting momentum strategies. Conrad and Kaul (1998) argue that the profitability of momentum strategies can potentially be explained by the cross-sectional variation in expected returns. Specifically, based on the empirical decomposition of profits, bootstrap and Monte Carlo simulations and alternative estimates, they find that the cross-sectional differences in mean returns play a key role in momentum profitability. Moskowitz and Grinblatt (1999) find that the momentum strategies are significantly less profitable when they control for industry momentum; however, when they buy past winning industries and sell losers, they yield high profits. Accordingly, they claim that industry-based momentum strategy generates more profits than individual stock momentum strategy, and that the significant component of firm-specific momentum returns can be explained by industry factors. Inconsistent with their arguments, the evidence in Grundy and Martin (2001) suggests that neither cross-sectional differences in expected returns nor industry effects are important determinants of the momentum phenomenon. In order to test the Conrad–Kaul conjecture, they use each stock as its own control for risk; Grundy and Martin (2001) find that even after subtracting each stock's mean return from its return during the investment period the mean return of momentum strategy still remains economically and statistically significant. Moreover, to address the contrary evidence of the Moskowitz-Grinblatt conjecture, they claim that although the returns of industry-based momentum strategy are consistent with an intra-industry lead-lag effect, industry momentum alone does not explain the profitability of momentum trading strategies.

Cheng and Roulac (2007) employ five groups of variables to demonstrate the multi-dimensional complexity of REIT companies and to investigate the predictability of REIT returns. The multifactor approach is based on a set of firm-specific factors: risk factors, liquidity factors, expensiveness, return history and profitability. The empirical result shows that their model is able to predict the momentum effect with fairly high consistency, and the fundamental characteristics of the "winners" versus the "losers" have a substantial explanatory power for the REIT momentum performance. However, this work raises questions regarding the validity of market efficiency, since the analysis contradicts and challenges the efficient market hypothesis. This point remains to be addressed by further study.

Derwall et al. (2009) point out that the conventional factor models that control for beta, size, book-to-market and common stock momentum factor significantly underestimate the momentum effect in the REIT industry. Their result is consistent with the findings of Fama and French (1996) that a three-factor model of returns fails to explain intermediate-horizon price momentum (see Rouwenhorst, 1998). Hung and Glascock (2008) study the REIT momentum in different market states. They report that the momentum of US REITs is higher during up markets; furthermore, the higher returns are not accompanied with higher risk, which supports the findings of previous research that momentum returns are not explained by risk. In sum, they conclude that the momentum returns of REITs can be explained jointly by a time-varying factor (market state) and a cross-sectional variance in dividend yields. In a later work, Hung and Glascock (2010) apply a GARCH-in-mean model to test asymmetric volatility effect in momentum returns in REITs. Additionally, they investigate whether idiosyncratic volatility and liquidity play a significant role in REIT momentum returns. They find that the momentum returns in REITs display asymmetric volatility, and are positively related. Furthermore, losers have higher levels of idiosyncratic risk than winners; the difference between them is statistically significant, which can contribute to momentum. Moreover, losers' returns are negatively related to their idiosyncratic risks, whereas winners' are positively related, and investors do not require a higher risk premium for holding losers' idiosyncratic risks; consequently, their low risk premia help to explain their low returns. Finally, they find a positive relationship between momentum and liquidity, which is measured by turnover.

In a recent study, Fama and French (2012) examine the return patterns in developed markets in North America, Europe, Japan, and Asia Pacific. They find strong momentum returns in all regions except Japan. Their new evidence focuses on how the international value and momentum returns differ with firm size, and reveals that value premia decrease from smaller to bigger stocks, except in Japan. Meanwhile, the momentum returns are also larger for small stocks, but no momentum returns are observed in any size group in Japan. Additionally, the authors investigate whether the value and momentum effects in average returns are captured by empirical asset pricing models, and whether these models explain that the asset pricing is integrated across regions. In the test of the global CAPM, three-factor and four-factor models on the value and momentum portfolio returns, only the four-factor model is passable for average returns on global size-B/M and size-momentum portfolios. Although the result is good for global models and integrated asset pricing, all three global models fail to explain regional returns. Specifically, the local four-factor model performs better than the other two models when explaining the value returns; however, it performs poorly on the size-momentum portfolios, and the other two models are even less successful than the four-factor models.

4.2.4 Momentum and Behavioural Finance

It would appear that the most credible proposed rationale for the momentum premium is to be found in behavioural explanations regarding the under-reaction and overreaction behaviour of investors. According to the overreaction hypothesis, Delong et al. (1990) explain that when investors are over optimistic, they tend to overreact to events by buying “winner” stocks, and when they are over-pessimistic they sell “loser” stocks. Thus, even where there is a lack of fundamental information, “trend-chasers” reinforce movements in stock prices induced by positive (negative) feedbacks; as a result, both positive and negative returns for past winners and losers tend to be substantial.

Chan et al. (1996) provide evidence that a stock’s prior return and prior earnings information predict the drift in future returns over the next six and twelve months, while the drift cannot be explained by the conventional factors of market risk, size and book-to-market effects. Those stocks with low past returns will on average experience low future returns over intermediate horizons can be explained by the under-reaction theory. An earnings momentum strategy may benefit from under-reaction to information announcements related to short-term earnings, while a price momentum strategy may benefit from the market's slow response to a broader set of information, including longer-term profitability. Similarly, Barberis et al. (1998), Daniel et al. (1998), and Hong and Stein (1999), provide evidence that momentum profits arise from inherent biases in the way investors interpret information.

Daniel, Hirshleifer and Subrahmanyam's (DHS, 1998) overconfidence theory suggests that investor overconfidence can generate the observed momentum effect, and since the REITs are relatively more difficult to value in the later period, this momentum is likely to be stronger. Contrarily, Hong and Stein (1999) propose that momentum profits relate to the speed of the diffusion of information; the theory predicts that momentum should be stronger in the earlier period due to weaker analyst coverage. Consistent with the DHS (1998) overconfidence theory, Chui, Titman and Wei (2003) find that the REIT momentum effect is small and weak in the pre-1990 period; however, it becomes strong and prevalent during the post-1990 period. Additionally, they find that the positive returns of the momentum portfolio are reversed in the two years after the formation period, which suggests that the momentum profits are generated from delayed overreaction rather than by under-reaction to information.

In a recent study, Chui, Titman and Wei (2010) use international data to examine the extent to which the momentum effect is generated by behavioural biases. Using an "individualism" index reported by Hofstede (2001), based on survey evidence from 50 countries,[39] they examine whether momentum profits are greater in those countries where investors are likely to exhibit the psychological biases discussed in the behavioural finance literature. Their evidence indicates that investors in different cultures interpret information in different ways and are subject to different biases; consequently, culture can have an important effect on the stock price momentum, which is consistent with the idea that individualism is positively associated with trading volume and volatility, as well as with the magnitude of momentum profits.

[39] According to Hofstede (2001), "individualism" reflects the degree to which people focus on their internal attributes, such as their own abilities, to differentiate themselves from others.

4.2.5 Investor Sentiment and REIT Momentum

As we have documented, the phenomenon of REIT price momentum has been investigated in many studies, and has been found to be significant in different asset classes and markets. The controversial explanations for REIT price momentum can be classified into three general categories: theories of market frictions (Hong and Stein, 1999), theories of time-varying expected returns (Johnson, 2002), and behavioural theories of market inefficiency (Daniel, Hirshleifer and Subrahmanyam, 1998). The investor sentiment explanation stems from the DHS (1998) behavioural theory, which refers to whether an individual feels optimistic or pessimistic about future returns for whatever extraneous reason; in this theory, DHS (1998) suggest that the momentum effect is generated by investor overconfidence and self-attribution bias. We consider whether the psychological theories may provide an adequate explanation for price momentum by examining the relationship between investor sentiment and REIT price momentum. This study contributes to the existing literature by being the first to examine whether direct measures of investor sentiment, which proxy for unsophisticated investors' trading activities, affect the momentum returns of REITs, and to what extent these investors' behavioural biases impact on the short-/long-run momentum.

4.3 Methodology and Data

Our data sample comprises publicly traded REIT between 2000 and 2012.[40] There are 226 REITs including equity, mortgage, and hybrid are listed in the NYSE, AMEX, and NASDAQ, however we select the REITs that have return data available in the Bloomburg during the sample period. 110 REITs monthly stock returns and market index returns over the sample period are obtained from the Bloomburg as well as the Consumer Board (CB) Consumer Confidence Index.

The measures of investor sentiment we adopt is the monthly time series data of consumer confidence index which is constructed by the CB, which has been published on the last Tuesday of each month since 1967.[41] Although it is considered as an index, this report is the questionnaire sent to around 5,000 households by mail with about 3,500 respond which change each month. The participants are asked to respond to five questions about their perception for the economy.[42] For each question, the CB calculates the scores based on the possible three answers the participants give which are positive, negative or neutral. This proportion is benchmarked to the average of the same proportions that occurred in the year 1985, which is assigned a CCI value of 100. This benchmarked number is then the value of the headline Consumer Confidence Index for that month. The CCI index is one of the ten

[40] We select this sample period due to the restriction of formatting the momentum portfolios, not enough REITs are available before the year of 2000.
[41] This survey began on a two-month survey basis; the monthly data comes from 1977.
[42] The questions are: current business conditions; business conditions six months hence; current employment conditions; employment conditions in the next six months; their own total family income in the next six months.

leading economic indicators published by CB; many previous studies use this index as the predictor of investors' behavior.[43]

Our study follows the methodology of forming momentum portfolios of Jegadeesh and Titman (1993). In order to increase the power of our test, we construct overlapping portfolios with holding period. Specifically, in any given month t, we sort all the REITs on their returns for the past J months. Based on these rankings, ten deciles of equally weighted portfolios are formed. The top decile is called the "loser" decile and the bottom decile is called the "winner" portfolio. Every month, the strategy buys the winner portfolio and sells the loser portfolio, holding this position for K months. Further, we close out the position initiated in the month t-K in both the winner and loser portfolios. Therefore, under this strategy, in any given month, we revise the weights on 1/K of the REITs in the entire portfolio and carry over the rest from the previous month.[44]

In order to mitigate the effects of macroeconomic conditions from the CB index, McLean and Zhao (2009), Antoniou et al (2010) use six macroeconomic indicators to perform a regression with this monthly index which are: growth in industrial production, real growth in durable consumption, non-durable consumption, services consumption, growth in employment and an NBER recession indicator. Finally, they save the residuals from the regression to be the sentiment proxy. Moreover, to test whether a given formation period is optimistic or

[43] See Ludvigson (2004) for household spending activity, Fisher and Statman (2003) for the investor optimism, Lemmon and portniaguina (2006) , Antonio et al (2010) for investor sentiment

[44] For example, for the 6-month holding period strategy (J,K=6), in any given month t+1, the winner portfolio is constructed by 1/6(winners from t-1) + 1/6(winners from t-2) + … + 1/6 (winners from t-6), and loser portfolios are formed in the same approach. Month t is skipped.

pessimistic, Antoniou et al (2010) use the rolling average of sentiment level for the three months prior to the end of formation period. They report results by dividing the investor sentiment states into two different classifications as optimistic and pessimistic to ensure the investigation is not sensitive to the definition of the sentiment states. If the three-month rolling average sentiment in months t belongs in the top 30% of the sentiment time series, then this formation period is considered as optimistic and vice versa. Addition to this, 20% as breakpoint to classify optimistic and pessimistic periods will be used as well for robustness.

In order to examine the long-run performance of momentum portfolios, we focus on 6-month formation/holding period strategy. Followed by the approach Jegadeesh and Titman (2001) used, we define an event time which is equal to 13 months following the initial formation date. Then we hold this portfolio for six years to check its performances in the optimistic formation periods and pessimistic formation periods individually.

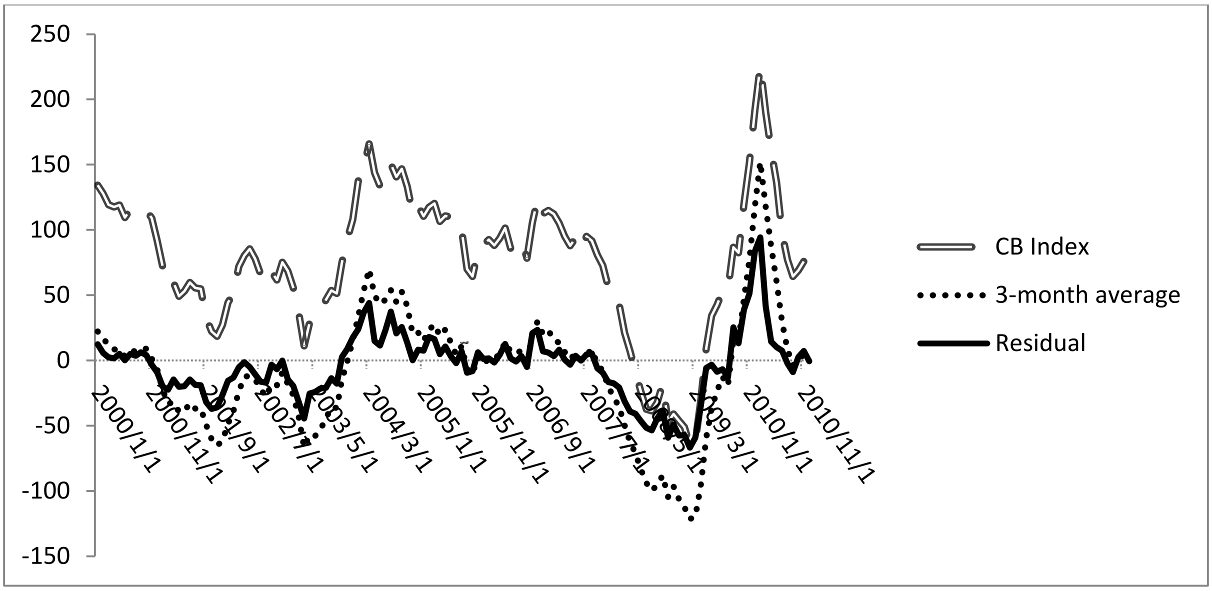


Figure 4.1 Investor sentiment from 2000-2010

Notes: This figure shows the raw data of consumer confidence index provided by CB; the residual from regress the CB index on the macroeconomic variables; the 3-month rolling average of the residual respectively.

As provided by Figure 4.1, we may find three investor sentiment indexes exhibit extremely similar performance during our sample period from 2000 to 2010. The sentiment falls from the beginning of our sample and forms a short time peak in 2002. From 2003, the sentiment rises substantially in one year; this wave lasts for about five years without huge fluctuations. However, from the end of 2006, the index drops dramatically to the 10-year bottom, as our knowledge, this is cause by the financial crisis which is generated around that time period. Interestingly, the investor sentiment reaches historically high in the two years' time, but it fails to last for a long time. Besides, we also observed that the 3-month rolling average of the residual, which will be the sentiment proxy in the following work, performs considerably close to the CB index.

Table 4.1 exhibits the descriptive statistics for the sentiment index. In this table, Panel a shows the raw data from the CB index, whereas Panel B shows our constructed 3-month rolling average residuals from the regression.

Table 4.1 Descriptive statistics for the investor sentiment

Mean	σ	Q1	Median	Q3	Minimum	Maximum	N
Panel A: CB consumer confidence							
84.77	13.27	71.45	87.65	91.67	55.32	112.48	132
Panel B: CB consumer confidence orthogonal to macroeconomic variables							
32.15	19.87	13.29	48	57.23	-61.17	76.3	132

Table 4.2 presents our REITs characteristics of the sample over period. We identify the winner/losers by using 20% and 30% breakpoint respectively, mean return is the average monthly return of REITs, S.D. of return is the monthly standard deviation of REIT returns, the average market capitalization, average monthly total shares traded and average monthly turnover are shown as well. We also provide the differences between winner and loser portfolio. In the sample, we have 110 REITs with the average 3% monthly return, and 7.36% monthly standard deviation. When we use two different breakpoints, we find that the winners always have a higher market capitalization than losers; the difference is 0.42 million of dollars by the 20% breakpoint and 0.48 by the 30% breakpoint. In terms of the liquidity, we observed that the trading volumes are fairly close in the two groups; however the winners always have better turnover than the losers.

Table 4.2 Descriptive statistics for the REIT sample from 2000-2010

Panel A:20% breakpoint	Entire Sample	Winners	Losers	Difference(winners-losers)
No.of REITs	110	22	22	
Mean Return	3.01%	6.22%	-3.40%	9.62%
S.D.of Return	7.36%	11.92%	13.12%	
Market capitalization	1.64m	1.25m	0.83m	0.42m
Volume	32993	35820	34921	899
Turnover	0.79	0.93	0.84	0.09
Panel B:30% breakpoint				
No.of REITs	110	33	33	
Mean Return	3.01%	4.15%	-2.64%	6.79%
S.D.of Return	7.36%	9.26%	10.71%	
Market capitalization	1.64m	1.72m	1.24m	0.48m
Volume	32993	34245	33189	1056
Turnover	0.79	0.82	0.8	0.02

4.4 Empirical Results

4.4.1 Investor Sentiment and REIT Short-run Momentum

Followed by Antoniou et al (2010), we investigate the REIT momentum strategies under two different sentiment periods. We define the top/bottom 30% (20%) of the rolling average sentiment as optimistic/ pessimistic periods, which can be considered as investors are positive/negative about future market conditions. We also use the widely recognized approach to construct the momentum portfolio by a six-month ranking period (J) and holding periods (K) for three, six and twelve months.

Table 4.3 provides us the six-month REIT formation portfolios for holding different time periods. From the 30% breakpoints, we find that in all three holding periods the average monthly momentum profits are significant in the optimistic periods; this suggests that when the investor sentiment is high, the momentum profits are very sensitive. However, this pattern cannot be found in the pessimistic periods, which shown to be statistically insignificant. Specifically, in the three months holding period, the monthly momentum profits are at an average level of 6.24% in the optimistic periods, whereas this figure turns to be much lower to an average level of 2.69% in the pessimistic periods. When the holding period extends to six months, the average monthly profits are 5.40% in optimistic states and declined to 1.84% in the pessimistic states. The corresponding average monthly momentum profits are 4.57% and 0.31% respectively in the longest twelve months holding periods. This result is consistent with Gutierrez and Hammeed (2004) who suggest that momentum profits depend on whether the economy has been expanding or contracting.

Table 4.3 Momentum Profits and Investor Sentiment

		Momentum Portfolio											
		1=Sell	2	3	4	5	6	7	8	9	10=Buy	Buy-Sell	[t-stat.]
		Panel A:30%-30% Sentiment States											
Panel A1:J=6,K=3													
Optimistic	(n=79)	-0.91	1.66	2.95	3.37	3.69	3.78	4.08	4.26	4.54	5.33	6.24	[7.65]
Pessimistic	(n=31)	3.29	5.34	5.95	5.48	5.34	5.74	5.27	4.87	4.62	5.99	2.69	[1.85]
											Opt.-Pes.	3.55	[1.98]
Panel A2:J,K=6													
Optimistic	(n=83)	-0.46	1.55	2.44	2.80	3.19	3.39	3.72	3.86	4.36	4.94	5.40	[6.59]
Pessimistic	(n=27)	3.68	4.39	5.08	5.25	5.13	5.19	5.22	4.67	4.58	5.52	1.84	[1.06]
											Opt.-Pes.	3.56	[2.39]
Panel A3:J=6,K=12													
Optimistic	(n=90)	0.81	2.48	3.49	3.85	4.39	4.61	4.96	5.18	5.41	5.38	4.57	[8.55]
Pessimistic	(n=11)	6.69	8.06	8.37	6.89	7.96	5.47	7.95	7.36	7.39	7.00	0.31	[0.32]
											Opt.-Pes.	4.26	[2.63]
		Panel B:20%-20% Sentiment States											
Panel B1:J=6,K=3													
Optimistic	(n=88)	-1.02	1.66	2.87	3.21	3.51	3.62	3.89	3.96	4.27	4.92	5.94	[6.32]
Pessimistic	(n=22)	5.82	7.18	6.38	6.58	7.96	4.65	7.38	6.37	6.14	8.13	2.31	[0.94]
											Opt.-Pes	3.63	[1.99]
Panel B2:J,K=6													
Optimistic	(n=94)	-0.76	1.28	2.30	2.60	2.96	3.19	3.48	3.65	4.05	4.61	5.37	[6.21]
Pessimistic	(n=16)	7.04	7.93	8.39	7.69	7.24	8.15	6.97	7.64	7.14	6.71	-0.33	[-0.96]
											Opt.-Pes.	5.70	[2.36]
Panel B3:J=6,K=12													
Optimistic	(n=100)	0.39	1.70	2.40	2.69	3.07	3.17	3.39	3.55	3.71	4.51	4.12	[7.98]
Pessimistic	(n=10)	10.56	8.62	9.37	7.69	9.36	9.57	8.36	9.45	9.57	9.32	-1.24	[-1.36]
											Opt.-Pes.	5.36	[2.98]

Note: This table presents average monthly returns in percentages for price momentum strategies involving all 110 REITs for the time period 2000 until 2010. At the beginning of each month all stocks are ranked based on their cumulative returns over the previous *J* months. Portfolio 1 includes the loser stocks and portfolio 10 the winner stocks. The winner stocks are bought and the loser stocks sold, and this position is held for *K* months. Monthly holding period returns come from overlapping strategies and are computed as an equal- weighted average of returns from strategies initiated at the beginning of this month, and the previous *K-1* months.

Another finding of Panel A is that there is a ascend trend in all three holding periods during optimistic sentiment states. The returns of momentum portfolios in pessimistic periods cannot hold this pattern which seems the highest return are from the middle of the portfolios. Specifically, the interesting result is that the returns of all the momentum in the pessimistic sentiment states are much higher than those in the optimistic sentiment state. This is because the investors may overestimate/underestimate the negative/positive information when their sentiment is low/high, lead to a lower/higher trading price.

From Panel B we can find that in terms of pattern, it performs fairly close to the Panel A, the significant momentum profits can be found only in the optimistic states. However, the corresponding absolute value of each momentum portfolio is higher than those in Panel A. Since this panel is based on a more extreme sentiment periods, we may propose that the REIT momentum returns are positively related to the market. Further, the average monthly profit seems to be lower in the 20% sentiment breakpoints. Overall, our result is consistent with Antoniou (2010) that in the high sentiment periods, investors ignore the negative events about loser REITs and due to short-selling constraints, arbitrage is not existed.

4.4.2 Sentiment, Momentum and Liquidity

Baker and Stein (2004) document that market liquidity can be a sentiment indicator. They find that both turnover and the equity share are noisy measures of the liquidity. In numerous other studies, Baker and Wurgler (2007), Boot et al (2008), Cherkes et al (2009), Boot (2013) also consider the liquidity is linked to investors' behaviour,. Lee and Swaminathan (2000) suggest that there is an important relation between momentum and liquidity which is proxied by the trading volume. Specifically, they find that firms with high (low) past turnover ratios[45] earn lower (higher) future returns, and have consistently more negative (positive) earnings surprises over the next eight quarters. Glascock and Hung (2009) find a positive relationship between the REIT momentum and the liquidity with is measured by turnover rates.

Further to these studies, we investigate whether the high/low liquidity confines the level of sentiment effect on the momentum portfolios. We construct momentum portfolios as stated before and additionally, in the formation period, we rank all the REITs based on their monthly turnover (calculated by trading volume/ shares outstanding). According to the turnover rates, we classify the liquidity measures into three groups: the first 30% highest turnover as high, the following 40% as middle and the last 30% is the low. Then we test the ten momentum groups and three liquidity groups during optimistic and pessimistic formation period respectively.

Table 4.4 shows the regression result for the momentum returns under different liquidity groups during two sentiment state periods. Panel A and Panel B present two different breakpoints for optimistic periods and pessimistic periods of the rolling average sentiment, respectively.

[45] They use trading volume and a proxy of liquidity and in the test, the turnover ratio is a measure of trading volume.

Table 4.4 Momentum Profits, Investor Sentiment and Trading Volume

		Momentum Portfolio											
		1=Sell	2	3	4	5	6	7	8	9	10=Buy	Buy-Sell	[t-stat.]
						Panel A:30%-30% Sentiment States							
Panel A1: High Vol.													
Optimistic	(n=83)	-1.48	1.18	2.05	2.36	2.74	3.19	3.57	3.72	4.29	5.24	6.72	[6.59]
Pessimistic	(n=27)	1.52	3.65	4.18	4.19	4.22	4.22	3.99	4.07	4.37	4.77	3.25	[1.63]
											Opt.-Pes.	3.47	[1.52]
Panel A2: Mid. Vol.													
Optimistic	(n=83)	-0.30	2.24	3.19	3.38	3.80	3.95	4.14	4.44	5.09	6.04	6.34	[6.58]
Pessimistic	(n=27)	3.46	5.01	5.89	6.08	6.16	6.01	5.73	5.89	5.89	6.08	2.62	[2.13]
											Opt.-Pes.	3.72	[1.36]
Panel A3: Low Vol.													
Optimistic	(n=83)	0.87	2.39	3.34	3.80	4.22	4.45	4.75	5.09	5.66	6.30	5.53	[6.39]
Pessimistic	(n=27)	5.80	6.38	6.80	6.08	6.73	6.54	6.68	7.31	7.22	7.49	1.76	[0.95]
											Opt.-Pes.	3.77	[1.92]
						Panel B:20%-20% Sentiment States							
Panel B1: High Vol.													
Optimistic	(n=94)	-1.82	0.79	1.55	1.87	2.36	2.63	3.02	3.06	3.56	4.43	6.25	[7.36]
Pessimistic	(n=16)	5.95	7.16	7.81	7.38	7.24	7.16	6.52	6.66	6.77	6.80	0.85	[1.63]
											Opt.-Pes.	5.40	[1.52]
Panel B2: Mid. Vol.													
Optimistic	(n=94)	-0.61	1.73	2.74	2.92	3.35	3.46	3.64	3.92	4.50	5.53	6.14	[8.63]
Pessimistic	(n=16)	7.67	8.89	9.10	9.12	9.11	8.71	8.28	7.96	7.94	8.09	0.42	[0.34]
											Opt.-Pes.	5.72	[2.63]
Panel B3: Low Vol.													
Optimistic	(n=94)	0.72	2.01	3.02	3.53	3.86	4.03	4.36	4.79	5.29	5.97	5.25	[6.42]
Pessimistic	(n=16)	9.32	9.54	9.43	9.36	8.96	8.57	8.42	8.57	8.28	9.85	0.53	[0.34]
											Opt.-Pes.	4.72	[1.99]

From the evidence of 30% breakpoint, we may find that the sentiment effect can be captured in all the liquidity portfolios. Specifically, during optimistic periods, in the high turnover rate group, the momentum profit is 6.72%, which is the highest among the three liquidity portfolios, this figure drops from the highest turnover rate group to the lowest groups by descend order, the middle one is 6.34% and the low turnover rate group is 5.53%. The pattern in the pessimistic periods exhibits the similar performance, with the highest profit of 3.25% and lowest 1.76% and the middle one is 2.62%. Furthermore, we can observe that in the

Panel A1 the momentum profits reduce to an average monthly return from 6.72% in optimistic periods to 6.34% in pessimistic periods. In the other two groups, the corresponding figures are all declined from optimistic periods to pessimistic periods.

In the panel B of 20% breakpoints, we find that the average monthly momentum returns for each liquidity group are lower than 30% breakpoints. The differences are more pronounced in the pessimistic periods which are declined substantially, particularly, we find that there is a negative return of -0.53% in the Panel B3 during pessimistic periods. However, the general trends are same as our 30% breakpoints test; the results show that the high turnover rates group has more momentum profits than the middle and low turnover rates group. The differences between two sentiment periods in each liquidity group are more significant in the 20% breakpoints.

Our results show that the sentiment effect is captured in all the liquidity groups. The momentums returns are positively related to the turnover, which is performed as higher turnover REITs have more profitable returns. We can also confirm that winners/loser have higher/lower risk premia to liquidity risk, causing momentum returns. The findings are consistent with previous works and even stronger than their result which has been Hung and Glascock (2009). However, in the pessimistic periods, the momentum returns of liquidity portfolios seem to be not significant with investor sentiment, this finding is consistent with Antoniou et al (2010) for testing the sentiment effect on the common stock momentums. In sum, the REIT momentum returns are sensitive to the liquidity, and they are positively related, however, this result is only significant during the optimistic periods when the sentiment is high.

4.4.3 Sentiment, Momentum and Size

Regard the size, LST (1991) conjecture that the smaller stocks are predominantly traded and held by individual investors, so the changes in their sentiment should be correlated with the returns on small capitalization stocks. The small firm effect based on investor sentiment story has been further investigated by Swaminathan (1996) and Nagel (2005). Both of their long horizon forecasting regressions demonstrate that the future excess returns on small firms can be predicted by the investor sentiment. In this part, we discuss whether the REIT momentum profitability, is affected by the size of company.

In order to classify the different REITs size group, we rank all the REITs at the end of the formation period based on the ascend order, we choose the first 50% REITs as the small capitalization firms and the other 50% are large capitalization firms, Based on the rolling average sentiment series, we define the top 30% as optimistic periods and the bottom 30% are pessimistic periods.

Table 4.5 Momentum, Investor Sentiment and Firm Size

Momentum Portfolio													
		1=Sell	2	3	4	5	6	7	8	9	10=Buy	Buy-Sell	[t-stat.]
	Panel A:30%-30% Sentiment states												
Panel A1: Small Cap.													
Optimistic	(n=83)	-1.09	1.33	2.34	3.02	3.56	3.85	4.32	4.54	5.01	5.36	6.45	[8.75]
Pessimistic	(n=27)	3.06	4.71	5.90	6.26	6.44	6.51	6.19	6.52	6.34	6.08	3.02	[1.87]
											Opt.-Pes.		[1.26]
Panel A2: Larger Cap.													
Optimistic	(n=83)	1.51	2.48	2.95	3.24	3.17	3.31	3.53	3.65	4.10	4.86	3.35	[6.13]
Pessimistic	(n=27)	3.24	4.14	4.43	4.61	4.57	3.89	3.96	3.89	3.87	3.67	0.43	[1.01]
											Opt.-Pes.		[1.21]
	Panel B:20%-20% Sentiment states												
Panel B1: Small Cap.													
Optimistic	(n=96)	-1.48	1.04	2.09	2.84	3.35	3.61	4.07	4.36	4.72	5.08	6.56	[8.34]
Pessimistic	(n=24)	7.70	8.96	9.91	9.65	9.79	8.91	9.03	9.00	8.94	8.54	0.84	[1.36]
											Opt.-Pes.		[1.04]
Panel B2: Larger Cap.													
Optimistic	(n=96)	1.15	2.19	2.66	2.99	2.95	3.02	3.24	3.36	3.74	4.43	3.28	[3.79]
Pessimistic	(n=24)	6.73	7.16	6.98	7.02	6.98	5.80	6.01	5.69	5.83	5.46	-1.27	[-0.34]
											Opt.-Pes.		[1.85]

Note: This table shows momentum strategies conditional on the investor sentiment and firm size. Size is measured as price x shares outstanding at the end of the formation period. Size decile breakpoints are from Kenneth French's data library.

Then we try to find whether our momentum strategy is affected by the different capitalization. In the table 4.5, from Panel A, the momentum portfolios returns are increasing from -1.09% to 5.36% and the momentum profits is 6.45% for the small cap in optimistic periods. When comparing with the pessimistic periods, the momentum profits are declined to 3.02%, there is not a trend like in optimistic markets. However, all the winner and loser deciles have a higher return than in the optimistic periods. Panel B exhibits the same pattern as Panel A, interestingly, in the optimistic period, even the absolute vale of the figures listed in the Panel B are almost as the same as panel A. Regarding with the pessimistic periods, each portfolio returns are substantially higher than those in the optimistic periods, nevertheless, the momentum returns in this periods are dropped to a relatively low level comparing with the optimistic periods.

Overall, the result reports that the sentiment affects for both small and large REIT firms. Moreover, the evidence show that the sentiment impacts on the smaller REIT firms to a relatively higher level than large firms. The findings in this table are consistent with the argument of Nagel (2005), Baker and Wurgler (2006) that investor sentiment is hard to be valued in the smaller firms, thus more prone to subject estimation, then it will be more significant in these firms. The sentiment effect is strong and robust to firm size, although in the pessimistic periods, it is not significant, both small and large firms show significant price momentum in the periods of investor sentiment is optimistic.

4.4.4 Other Sentiment Measures

The University of Michigan Consumer Sentiment Index (MCSI) is produced by the University of Michigan and distributed by Thomson Reuters. The Index of Consumer Expectations is an official component of the US Index of Leading Economic Indicators. The MCSI is designed to analyses consumer attitudes toward the overall business climate, the state of personal finances, and consumer spending. The University of Michigan survey of consumer sentiment started in 1947 on a quarterly basis and turn to be a monthly basis from 1978. The survey is sent to 500 households, and the respondents are asked the following questions: (1) Would you say that you (and your family living there) are better off or worse off financially than you were a year ago? (2) Do you think that a year from now, you (and your family living there) will be better off financially or worse off, or about the same as now? (3) Now turning to business conditions in the country as a whole—do you think that during the next 12 months, we will have good times financially or bad times or what? (4) Looking ahead, which would you say is more likely—that in the country as a whole we will have continuous good times during the next five years or so or that we will have periods of widespread unemployment or depression, or what? And (5) Do you think now is a good or bad time for people to buy major household items? The MSCI is widely followed as the measure of investor sentiment which is documented by numerous papers, see Dominitz (2003), Ludvigson (2004), Golinelli (2004), Lemmon and Portniaguina (2006).

Baker and Wurgler (2006) examine the sensitivity of investor sentiment to the cross-section of stock return by using the monthly measure of constructing a combined multifactor investor sentiment index. They suggest that investor sentiment can be captured from various market-based variables that relate to investors' propensity to purchase stocks. They construct a sentiment time series using six sentiment-revealing variables: trading volume (measured as total NYSE turnover), dividend premium, closed-end fund discount, number and first day returns in IPOs, and the equity share in new issues. Because these variables are partly related to economic fundamentals, they regress each of these sentiment proxies against growth in industrial production, real growth in durable consumption, non-durable consumption, services consumption, growth in employment, and an NBER recession indicator, and use the residuals from this regression as the sentiment proxies. The overall sentiment index is the first principal component of the six sentiment proxies. For more detail on the construction of the index, see Baker and Wurgler (2006, 2007).[46] This time series is available on a monthly basis from 1966 to 2005.

Table 4.6 Momentum and different sentiment measures

		Momentum Portfolio											
		1=Sell	2	3	4	5	6	7	8	9	10=Buy	Buy-Sell	[t-stat.]
		Panel A:30%-30% Sentiment States											
Optimistic	(MCSI)	-0.91	1.26	2.31	2.81	3.08	3.42	3.64	3.89	4.36	4.83	5.74	[8.56]
	(BW)	-0.58	1.66	2.66	3.10	3.46	3.67	3.89	4.00	4.32	4.75	5.33	[7.21]
Pessimistic	(MCSI)	5.64	6.76	7.34	7.10	7.11	6.93	6.86	7.13	7.02	6.82	1.18	[1.52]
	(BW)	6.55	7.34	7.52	7.45	7.13	7.06	7.16	7.34	7.88	8.78	2.23	[0.36]
		Panel B:20%-20% Sentiment States											
Optimistic	(MCSI)	-0.28	1.82	2.80	3.18	3.54	3.67	3.94	4.27	4.62	5.04	5.32	[7.93]
	(BW)	-0.14	2.09	3.06	3.49	3.82	3.99	4.24	4.43	4.79	5.36	5.50	[7.21]
Pessimistic	(MCSI)	6.41	1.82	2.80	3.19	3.53	3.78	4.06	5.91	6.05	6.90	0.49	[1.53]
	(BW)	8.82	8.60	8.50	8.14	7.60	7.49	7.49	7.45	7.74	7.36	4.91	[1.13]

Note: This table present the momentum profits conditional on two different sentiment proxies. BW sentiment is measured using the monthly sentiment index constructed by Baker and Wurgler (2007), using trading volume (measured as total NYSE turnover), dividend premium, closed-end fund discount, number and first day returns in IPO's, and the equity share in new issues.

Table 4.6 reports the momentum results for optimistic and pessimistic periods, by using the Baker and Wurgler sentiment measure (BW) and MCSI survey based measure respectively.[47] Apart from the sentiment index changed by the BW and CCI, all the other constructions and calculation are the same as previous tables.

Consistent with our previous findings, the result from this table confirms that the performance of momentum profits under optimistic sentiment state remains significant even

[46] This index is available from Jeffrey Wurgler's website (http://pages.stern.nyu.edu/~jwurgler/).
[47] For the MSCI sentiment index, we apply the same approach as the CCI, which is the 3-month rolling average residual.

we change use the alternative sentiment indexes. When we focus on the MSCI sentiment index, we find that the momentum profits are significant in both 30% and 20% breakpoints. Specifically, the average monthly momentum profits are dramatically higher in the optimistic states with the figure of 5.74% than those profits in pessimistic state. Moreover, the momentum return profits cannot observe to be significant, which adds the support to our previous finds. In panel B, although each portfolio has higher returns than in panel A, the average monthly momentum return is even smaller than Panel A. The difference of the momentum profits between two sentiment states is close under the 30% and 20% breakpoints.

The BW sentiment measure adds another support to our previous finds. In the Panel A, where optimistic (pessimistic) periods are defined as those that fall into the top (bottom) 30% of the sentiment rolling average time series, the average monthly momentum profits are 5.33% in the optimistic states, this return is reduced substantially to 2.23% in the pessimistic periods. From Panel B, for the 20% breakpoints, this difference in two different sentiment states is narrow with 5.50% in optimistic periods and 4.91% in pessimistic periods. These findings support our precious study that the momentum returns are significantly related to the investor sentiment during the optimistic states. Further, the other choices of our sentiment index enhance the explanatory power for the sentiment effect on the REIT price momentums.

4.5 Conclusions

Stock price momentum has been extensively studied in the literature. Jegadeesh and Titman (1993) document that the U.S. stock market yields 12% annual return over the past 30 years using momentum trading strategy. Additionally, the authors suggest that these momentum returns are not a result of systematic risk of the securities. Chui, Titman and Wei (2003) also find significant momentum returns in Real Estate Investment Trusts (REITs) from 1982 to 2000 and Hung and Glascock (2008) find that REIT momentum returns are higher in up markets and REIT winner portfolios have higher dividend to price ratios.

However, Price momentum is an anomaly not captured by the Fama and French (1996) three-factor model. It has been linked to both rational and behavioural explanations. In this paper, we provide evidence on the validity of behavioural explanations by investigating the interplay between price momentum and investor sentiment.

In order to investigate the momentum profitability, we classified the formation period into two sentiment states as optimistic and pessimistic. The evidence indicates that when the sentiment is high, the REIT momentum profitability is substantial and significant; however, when the sentiment is low, the profits from the REIT momentum are much lower and not significant. We also examine the interplay between REIT liquidity and momentum profitability, particularly, we find that high REIT liquidity portfolios generate higher momentum returns, but this is only significant when the sentiment is optimistic. The firm size is also considered in this chapter, consistent with our previous findings, our evidence that momentum is generally larger for smaller companies confirms that the size effect is still available in the REIT industry. This is because the smaller companies are hard to value, which are more prone to subjective evaluations; the sentiment thus could be more significant in small size companies.

CHAPTER 5

CONCLUSIONS

5.1 Research Overview and Implications

Fund price deviations from fundamental value and the price momentum are the anomalies that cannot be well captured by the conventional finance models such as the Fama and French three-factor model. Attempts therefore have been made in the literature to find the plausible explanations. The recent research in this field is generally linked to both rational and behavioural elucidations. In this thesis, we follow the investor sentiment approach to provide a behavioural explanation of the fund market anomolies by way of estimating and analysing the empirical relationship between investor sentiment and fund anomalies, particularly the closed-end fudn puzzle, the ETF price movements and REITs' price momentum.

In chapter 2, we analyse the empirical evidence regarding the theoretical prediction that small investor sentiment has a significant impact on stock risk premium and the changing sentiment of individual investors explains the discounts of closed-end funds. Focusing on the UK market, we apply the time series regression on the augmented CAPM and the four-factor models. The econometrical formulation is fine-tuned by adding the sentiment factors to check if the return generating process of closed-end funds' stock is related to the sentiment. Our evidence is consistent with the view of LST (1991) that investor sentiment influences the risk of common stocks. According to our results, we argue against the findings of Elton et al

(1998), Doukas and Milonas (2004) who indicate that investor sentiment cannot be related to the stock return generating process. We find that the sentiment factor is significant when entering the return generating process and size does matter. Our estimation detects that investor sentiment is more prevalent in smallest sized portfolios than in other larger ones. It offers us additional insights into LST (1991) theory which claims that the sentiment influence is a small firm effect. When we investigate the patterns of return sensitivity to the sentiment factor in terms of sector indices and individual stocks, there is strong evidence that they are more sensitive to the sentiment factor due to higher individual ownership.

In chapter 3, we investigate whether measures of investor sentiment have a significant effect on the pricing of UK exchange traded funds and, if any, how such an impact varies with the varying characteristics of the stocks that UK ETFs hold. Particularly, in this study, we construct the sentiment index based on the put–call volume ratio which can be calculated using both the open interest of options and trading volume. Using a multi-factor model, the result suggests that the sentiment is an important factor which causes the UK ETF mispricing. However, there seems to be a negative relationship between the liquidity and the fund premium; both of them have a significant effect on ETFs. This finding is consistent with the argument that in more liquid makes the fund price would go higher, so that fund premium would be lower. Another finding is related to the momentum factor. We find that past price changes in NAVs (momentum) have a significant effect on the fund premium in almost all the regressions, indicating that the past information is not fully reflected in the current UK ETF prices and the past price changes can be persistent over time.

From Chapter 3, we document that betas obtained from the traditional multi-factor model could be statistically imprecise and may contain a fair amount of statistical noise due to a relatively low number of degrees of freedom and other statistical problems associated with the use of individual fund premiums. In this light, we adopt the Bayes-Stein sentiment beta estimates in further tests. The results indicate that for the contrarian sentiment traders, whose behaviour is such that they buy the securities when sentiment is low, and sell them out when the sentiment is high. The empirical outcome also shows that the contrarian and momentum traders cannot cancel each other. Moreover, the fund returns' sensitivity to investor sentiment varies across different ETF characteristics. Of particular note is the interesting finding that the smaller, younger ETFs are prone to be affected by sentiment.

In Chapter 4, we focus on whether investor sentiment affects the profitability of REITs' momentum strategies. In order to investigate this issue, we classify the formation period into two sentiment states, i.e. the optimistic and pessimistic states. Evidence unearthed indicates that when the sentiment is high, the REIT momentum profitability is substantial and significant. However, when the sentiment is low, the profits from the REIT momentum are much lower and not significant. We also examine the interplay between REIT liquidity and momentum profitability, to find that high REIT liquidity portfolios generate higher momentum returns, but this is only significant when the sentiment is optimistic. The firm size is also considered in this chapter. Consistent with our previous findings, evidence suggests that momentum profit is generally larger for smaller companies, which confirms that the size effect is still present in the REIT industry. This is because the smaller companies are hard to value, hence are more prone to subjective evaluations that tend to be biased. As a result, the sentiment could become more significant in small sized companies.

Overall, we capture the evidence that investor sentiment is statistically significant in explaining the fund anomalies in both the UK and US markets. The results are robust when we use different proxies measuring investor sentiment which are constructed in both the direct and indirect ways. When conditioning on the firm size, firm characteristics, market liquidity, market states, and other risk adjustments, the results are robust as well.

The results of this paper have a number of serious implications for fund market anomalies and investor rationality. Most importantly, if investor rationality characterized fund markets, the fund price would not be excessively deviated from its fundamental value. Although the fundamental value has its easily captured indicators, the pricing of funds are still inconsistent with hypothesis of market efficiency. Holding the fund is risker than holding its underlying assets directly and this risk is systematic thus cannot be diversified, the investors must require a higher returns on the funds than the same underlying portfolio purchased directly. This means the fund must, on average, deviate from its fundamental value.

Secondly, the changes of the fund deviation are highly correlated. This is because they are driven by the same investor sentiment, this sentiment not only impacts on the funds but also the underlying assets. The observation that the smaller, younger, lower institutional ownership funds are more sensitive to investor sentiment, since these funds are hold predominantly by the irrational individual investors, these investors trade in the fund market infer too much from small pieces of information, they are likely to forecast price instead of fundamental value, consequently, observing price changes might be mistakenly over-informative.

The third implication of our research on the REIT momentum is that when the investor sentiment is high, the momentum profitability is substantial and significant, but when the sentiment is low, the profits from the REIT momentum are much lower and not significant. Because if investors are very optimistic, they are more miscalibrated, when noise traders are particularly optimistic about the REIT, entrepreneurs can profit by putting assets together into REIT and selling them to the noise traders, which leads to the momentum in securities. Additionally, the smaller, younger, lower institutional ownership funds can generate more momentum profits, as they are hard to value and therefore are more prone to subjective evaluations, and produce more momentum profits.

5.2 Limitations and Future Research

Although this work makes a critical contribution to a better understanding of the fund anomalies in terms of CEF puzzle, ETF price premium, REIT price momentum, there are several limitations existing, which are listed below as the areas for future research.

First, several kinds of event studies have been linked to the investor sentiment and fund performances such as in the studies of IPO patterns (Cherkes, 2003) and managerial performance (Chay and Trzcinka, 1999; Berk and Stanton, 2007). Thus, the event studies on the other aspects of the sentiment-fund performance nexus are a promising avenue for future research. Currently, this methodology is generally ignored by researchers. Other topics, such as board structure of the corporate, mergers and acquisitions and corporate diversification, and their roles in fund market anomalies may also be worth of future research.

Second, in the UK market, the increasing popularity of the fund industry could well mean that fund returns and characteristics are interesting influences to be explored in testing the fund price performance. Their roles could be more pounced and insightful. Additionally, due to data availability problems in the UK, it is not easy to construct a combined sentiment proxy such as the one used by Baker and Wurgler (2006) work for the US market. The sentiment index construction remains an area requiring further studies because the investor sentiment can be expressed in many different ways and there remain rooms for improve the measurement of investor sentiment.

Finally, the model we proposed in the thesis may be extended by incorporating more additional explanatory variables. Although the existing models and the variables we use in this study are relevant to the model specification and the estimation results are robust, in order to obtain a more precise evaluation, the information related to the fund managers and more macroeconomic factors may need to considered to address the sentiment issue which illusive by its nature. Moreover, as we discussed in the thesis, investor sentiment may vary across different markets and geographical locations. It will be very promising for future studies on the fund market to extend their research coverage to consider more markets around the world.

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